Review

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Keywords: optical neuromorphic processing; integrated optics; machine learning; artificial intelligence

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Review on Integrated Photonic Neural Networks

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Abstract

Neural networks (NNs), inspired by the biological visual cortex, have been widely applied in computer vision, natural language processing, and beyond. As Moore's Law approaches its physical limits, photonic neural networks (PNNs), which leverage photons rather than electrons as information carriers, have emerged as a promising technological advancement. With ultrafast speeds and ultralow energy consumption in ultra-high throughput, PNNs usher in a new generation of intelligent computing. Moreover, the advent of photonic integrated circuits (PICs) provides a compact and reliable hardware platform for computing, further advancing the development of PNNs. In this paper, we review recent advances in linear and nonlinear computation and integrated optical devices serving as fan-in and fan-out. We also summarize large-scale on-chip PNN and discuss the future challenges associated with their monolithic integration.

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Introduction

Deep learning, a rapidly developing breakthrough technology, is leading the change in science and technology [1,2]. It adopts NNs to extract the data representations by performing extensive algebraic operations on the input data, such as matrix multiplication and convolution, thereby creating an ever-increasing demand for computing performance.

In recent years, electronic hardware with higher performance has been developed to better support the computation of NNs, such as the tensor processing unit proposed by Google [3] and the Cambrian series acceleration chip launched by the Computing Institute of the Chinese Academy of Sciences[4].

Nevertheless, the size of integrated circuit devices is approaching the physical limit, accompanied by other phenomena such as quantum tunneling, parasitic effects, etc., which hinder further progress. Indeed, in the post-Moore age, traditional microelectronic computing chips based on Complementary Metal-Oxide-Semiconductor (CMOS) technology encounter a bottleneck in meeting the growing demand for computing power. Hence, the pursuit of novel computing and processing methods, along with their physical realizations, has garnered increasing attention.

PNNs, a deep fusion of optical information processing and neural network theory, aim to leverage the interaction between light and matter to map the network computation onto the optical field and utilize the transmission functions of different optical devices to perform computation, thereby executing specific tasks, as shown in Figure 1. PNNs have shown great potential in supporting the NNs computation due to their ultra-high bandwidth, low energy consumption, low latency, and high parallelism. While substantial progress has been made in developing PNNs implemented through discrete off-chip optical devices[6,7], integration remains the dominant approach for addressing the challenges of scalability, efficiency, and practical development within operational environments. In particular, the development of diverse material platforms has enabled the fabrication of various optical devices, driven by advancements in integrated photonics technology. This progress has significantly accelerated the realization of PNNs and other photonic-based technologies, paving the way for more efficient and scalable solutions in the field.

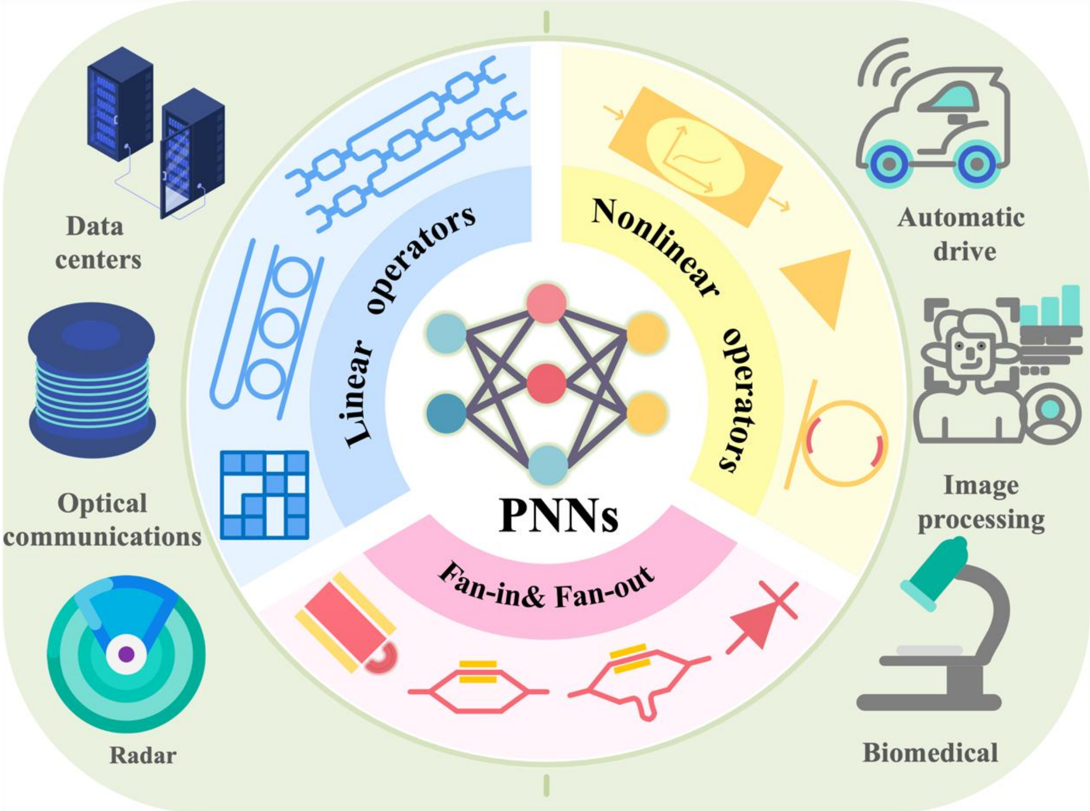

Figure 1. The components and applications of the PNNs.

In this review, we provide a comprehensive introduction to the three fundamental components of PNNs: linear operators, nonlinear operators, and data interfaces. We analyze recent advancements in these areas, highlighting researches that leverage various optical devices or materials. Additionally, we provide an overview of large-scale on-chip integrated PNNs and discuss the challenges associated with their further development.

Linear Operators

Linear operation is the fundamental computation in NNs, playing a crucial role in a wide range of AI tasks. Since each layer of NNs typically consists of neurons that perform linear mappings, a significant portion of the computational cost arises from performing large-scale linear operations. The light's high parallelism has the inherent advantage of performing linear operators, and such operations are already available in different photonic devices.

Linear operator based on Mach-Zehnder Interferometer (MZI)

As a fundamental passive optical device, a single MZI typically consists of two couplers and two interference arms. By applying external electronic control signals to the heaters deposited on top of each MZI arm, the device can be configured to provide independent power splitting ratios and relative phase shifts, making it a simple linear operator.

Any arbitrary unitary transformation can be realized by designing appropriate routing structures (e.g., triangular or rectangular) [8]. Furthermore, large-scale MZI calibration relies on various extensively studied algorithms[9–12], providing a solid foundation for implementing linear operators based on MZI[13–18].

2017, Shen et al. experimentally demonstrated the essential part of the concept using a programmable nanophotonic processor featuring a cascaded array of 56 programmable MZI in a silicon photonic integrated circuit and show its utility for vowel recognition (Figure 2a)[13].

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Theoretically, any matrix can be decomposed into one diagonal matrix and two unitary matrices using the singular value decomposition method. The optical attenuators can implement any diagonal matrix function, and the beam splitters and phase shifters can achieve any unitary matrix function. Thus, the training weight matrices of PNNs can be physically implemented one-to-one via integrated optical elements.

Besides the real-valued computation, some works reported complex-valued linear operators utilizing MZI mesh.

In 2021, Zhang et al. utilized both the phase and amplitude of light by cleverly assigning routes in the MZI mesh, implementing input preparation, weight multiplication, reference light, and coherent detection onto a single chip (Figure 2b)[14]. The work demonstrated relatively completed work such as logic gate operation, IRIS dataset category prediction, nonlinear data (circle and spiral) classification, and MNIST dataset handwritten digit recognition.

In 2022, Zhu et al. proposed an integrated chip diffractive neural network(DNN), using an MZI array to implement convolution operations in the complex field after finishing an optical discrete Fourier transform (ODFT) operation (Figure 2c)[15].

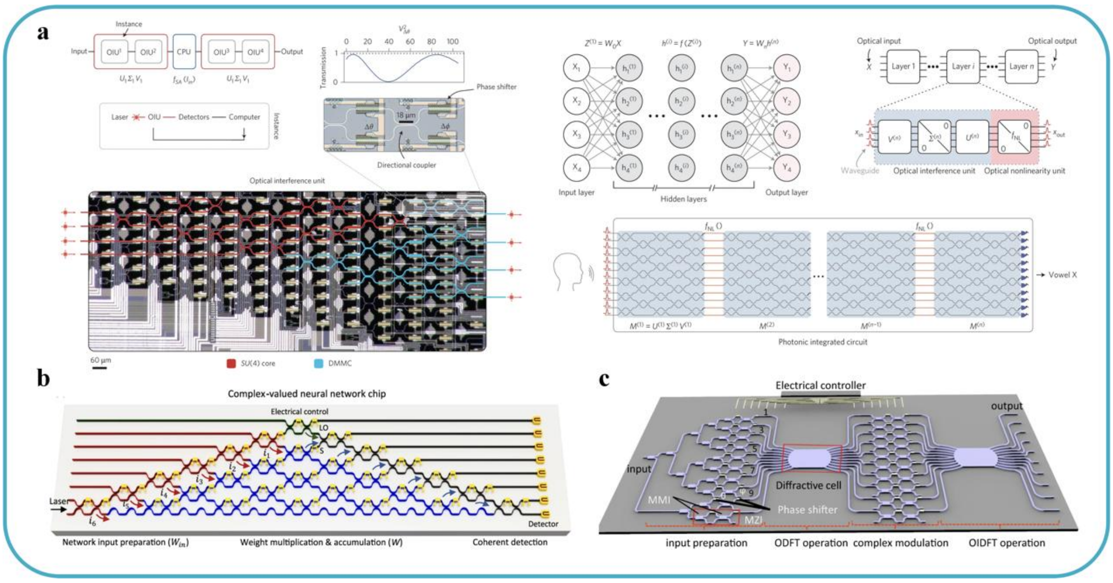

Figure 2. Linear operators based on MZI. a Programmable nanophotonic processor based on 56 MZI. b Complex-valued neural network chip based on MZI mesh. c On-chip DNN based on MZI array.

Linear operator based on microring resonator (MRR)

Compared to MZI, MRR generally requires more meticulous design efforts in optimizing coupling parameters to achieve sufficient extinction ratios. However, MRR-based architectures can perform precise linear operations through resonance wavelength tuning. This distinctive feature makes MRR particularly advantageous for implementing programmable linear operators.[19–29].

In 2016, Tait et al. conducted a detailed study on the MRR weight banks, including the principle of MRR, mutual channel crosstalk, and its design methods[19]. Afterward, they demonstrated a broadcast-and-weight system that is very significant in linear operators based on MRR weight banks (Figure 3a)[20]. Its core idea is that incoming WDM signals are weighted by reconfigurable, continuous-valued filters called photonic weight banks and then summed by total power detection. The works above provide theoretical support for using MRR weight banks in linear operators.

In 2021, Huang et al. fabricated MRR weight banks based on a silicon-on-insulator platform and demonstrated that they can complete nonlinear compensation assistance with electronic hardware (Figure 3b)[21].

In 2022, Bai et al. proposed a parallel photonic processing unit integrating MRR and delay lines and performing a convolution operator (Figure 3c)[22]. The add-drop MRR weight bank

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simultaneously performs spectrum slicing, kernel weight loading, and spectrum recombination, achieving a record-high weight precision of 9 bits.

To improve convolution parallelism, in the same year, Xu et al. proposed an integrated photonic tensor flow processor based on MRR and WDM (Figure 3d)[23]. The three weight banks were divided by two delay lines, and each weight bank included four MRR, which can weigh four different wavelengths. The team then used the same chip to implement analog spatiotemporal feature extraction, facilitating the further expansion of the application scene[24].

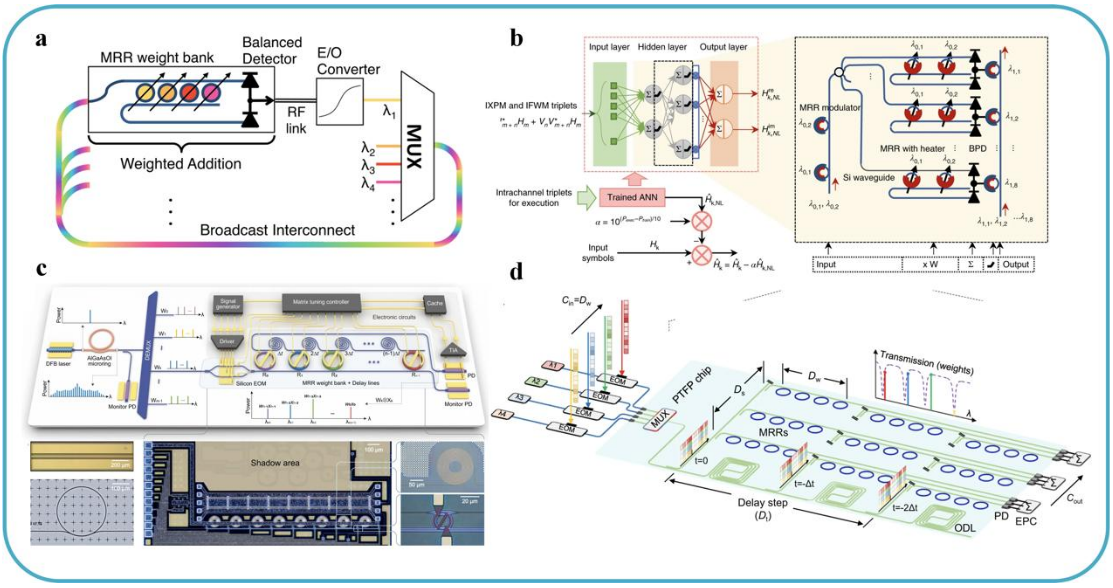

Figure 3. Linear operator based on MRR. a Broadcast-and-weight system based on MRR weight banks. b Nonlinear compensation based on MRR weight banks. c Integrated photonics processing unit based on MRR. d Integrated photonic tensor flow processor based on MRR.

Optical devices based on optical storage mediums

Significant progress has been made in the development of non-volatile memory devices integrating optical storage materials with waveguides for PNNs. Optical storage materials, such as phase-change materials (PCMs), can undergo rapid and reversible structural phase transitions under the influence of electrical or laser pulses, resulting in non-volatile differences in electrical or optical properties. These materials are considered one of the key candidates for enabling non-Von Neumann computing architectures. Several linear operators based on optical storage media have been proposed and extensively investigated.

Feldmann et al. developed a fully connected all-light peak neural network photon chip. Under the action of light pulses, the PCMs unit coupled to the waveguide structure controls the neuronal weight and performs summation operations on the multiple optical signals through the MRR array (Figure 4a)[30]. Afterward, they demonstrated that integrated photonics tore based on PCMs can perform at speeds of trillions of multiply-accumulate per second (Figure 4b)[31].

In 2023, Zhou et al. developed non-volatile electronically reprogrammable PCMs memory cells (Figure 4c)[32]. Variable Optical Attenuator (VOA) encodes image information in different wavelengths, electronically controlling weight based on PCMs cells, which can perform 4-bit weight encoding and low energy consumption per modulation depth. At last, the multiplication results were obtained by PD. The same year, Dong et al. proposed higher-dimensional in-memory computing with continuous-time data based on PCMs (Figure 4d)[33]. Inputting 3D array data into the photonic tensor core, whose basic building block is the MZI cascading PCMs memory. Specifically, using the MZI's route function to perform data summation, the PCMs' state is controlled to perform data weighting.

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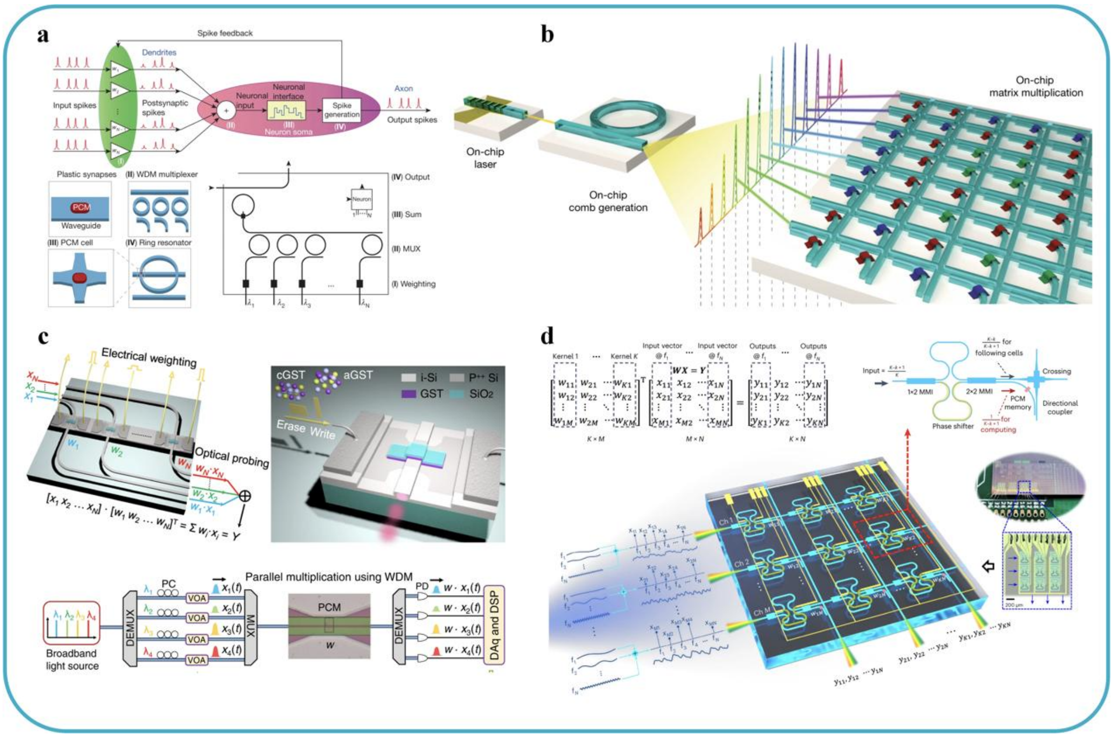

Figure 4. Linear operator based on optical storage medium. a All-optical spiking neuronsynaptic network based on PCMs. b Photonic in-memory computing based on PCMs units. c In-memory photonic–electronic dot-product engine based on PCMs. d Photonic tensor core based on PCMs.

Linear operator based on modulator array

Modulators are common devices for signal input. Notably, they function as linear operators only when a direct current (DC) bias voltage is applied. Based on this working mechanism, modulator arrays are also form a crucial architecture of linear operators[36–41].

In 2021, Xu et al. demonstrated that an optical coherent dot-product chip can implement sophisticated regression tasks (Figure 5a)[40]. The laser was split into seven branches, with one as a reference path for providing local oscillator light, and the other branches have two modulators. Utilizing modulators work in different models to perform signal modulation and computing matrix load.

In 2024, Moralis-Pegios et al. presented a 4x4 coherent crossbar structure and performed 1000 arbitrary linear transformations achieving a record-high fidelity of 99.997%±0.002 (Figure 5b)[41]. The main component device is a 50 GHz silicon germanium (SiGe)-based electro-absorption modulator, functioning as an input vector and transformation matrix.

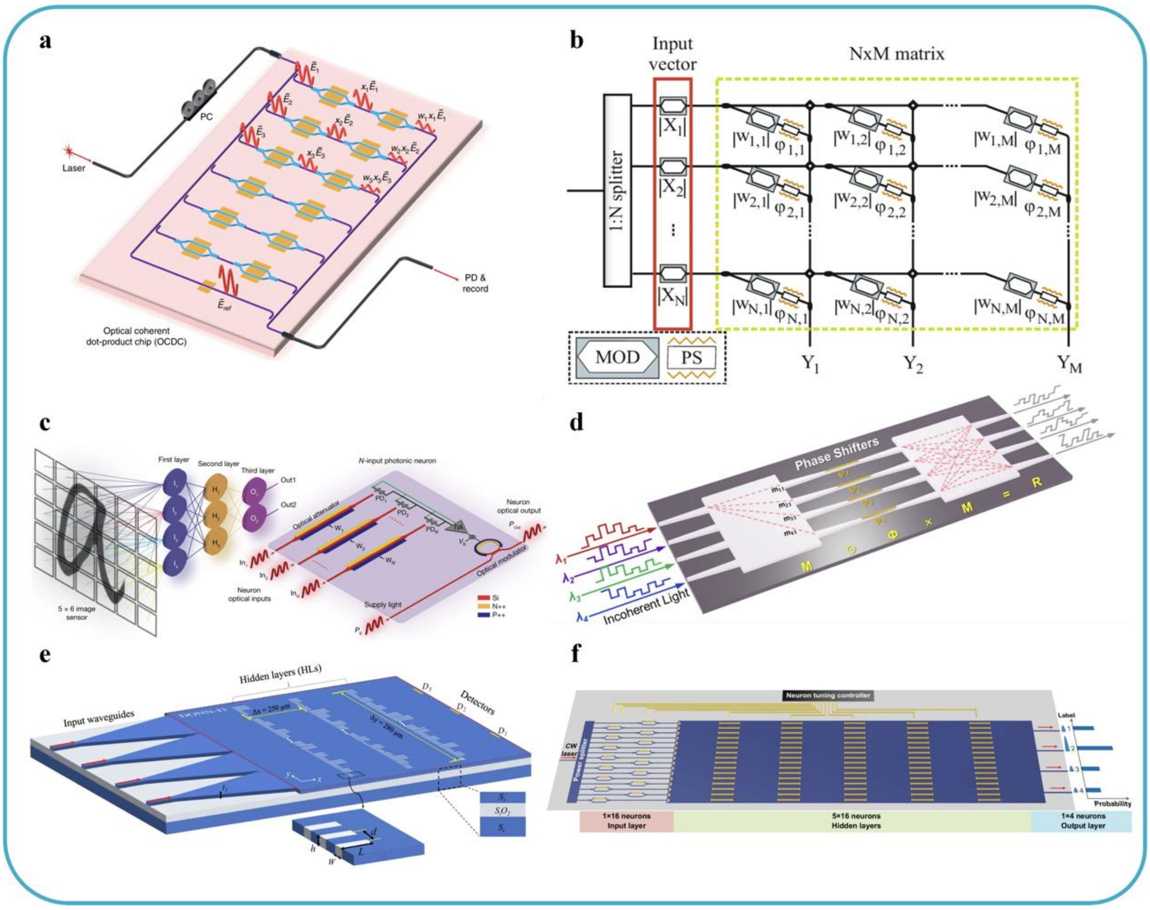

Figure 5. Linear operators based on modulator arrays other integrated optical devices, and on-chip diffractive metasurfaces. a Optical coherent dot-product chip based on modulator array. b On-chip linear operator based on N × M crossbar architecture. c PDNN based on PIN. d Parallel convolution processing unit based on MMI. e On-chip DONN architecture based on a 1D dielectric metasurface. f On-chip diffractive metasurfaces for multimodal deep learning.

Linear operators based on other integrated optical devices

Other devices, like multimode interference (MMI) P-doped-intrinsic-N-doped (PIN), can also perform linear operators, in addition to traditional optical devices[42–46]. These devices offer unique advantages in implementing linear computation, further expanding the range of tools available for photonic-based processing.

In 2022, Ashtiani et al. proposed an integrated end-to-end photonic deep neural network that performs sub-nanosecond image classification (Figure 5c)[42]. The linear part of this work was realized by tuning long PIN current-controlled attenuators; every attenuator can control the optical power to complete weight mapping respectively.

In 2023, Meng et al. designed and fabricated two MMI cells and four phase shifters to perform parallel convolution operations (Figure 5d)[43]. This work used 4×4 MMI's transmission function, four tunable phase shifters, and off-chip SOA to build the convolutional kernel. Ten-class classification of handwritten digits from the MNIST database is experimentally demonstrated.

Linear operator based on on-chip diffractive metasurfaces

On-chip diffractive metasurfaces have found widespread applications in diffractive optical neural networks (DONNs) due to their ability to perform linear computations by controlling the wavefront of reflected beams [47–52].

In 2023, Fu et al. fabricated 1-hidden-layer and 3-hidden-layer on-chip DONNs with footprints of 0.15 mm[2] and 0.3 mm[2] and experimentally verified their performance on the classification task of the Iris plants dataset, yielding accuracies of 86.7% and 90%, respectively. The on-chip DONN architecture is based on an integrated one-dimensional (1D) dielectric metasurface (Figure 5e)[51],

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which consists of a series of silicon slots filled with silicon dioxide; it represents the hidden layer (HL) in on-chip DONNs.

In 2024, Cheng et al. proposed and demonstrated a trainable diffractive optical neural network (TDONN) chip based on on-chip diffractive optics with massive tunable elements (Figure 5f)[52]. The TDONN chip includes one input layer, five hidden layers, and one output layer, and only one forward propagation is required to obtain the inference results without frequent optical-electrical conversion.

Nonlinear operator

Nonlinear computation is an essential component of neural networks, as introducing nonlinearity between linear layers is crucial for achieving optimal performance. Implementing nonlinear operations represents a significant step toward realizing all-optical computing. However, developing efficient and fully integrated all-optical nonlinearities remains a substantial challenge. Currently, nonlinear operators mostly rely on active devices[53–57] or nonlinear optical materials[58–60].

Realizing nonlinear processing through the photoelectric effects of active devices is a feasible approach. Numerous schemes have been proposed, leveraging modulators and photodetectors to achieve this functionality.

In 2021, Oh et al. released a Mott neuron based on vanadium dioxide (Figure 6a)[56]. The core of this work is to simulate the linear increment of the Relu activation function by transitioning vanadium dioxide from an insulator to a metal-semiconductor phase, effectively modulating its band gap. The study demonstrates the classification performance of Mott activation regions in recognizing handwritten digits within the LeNet-5 network.

In 2022, Shi et al. designed nonlinear germanium-silicon photodiodes to construct on-chip optical neurons and a self-monitored all-optical neural network (Figure 6b)[57]. With specifically engineered optical-to-optical and optical-to-electrical responses, the proposed neuron merges all-optical activation and nonintrusive monitoring functions in a compact footprint of 4.3 × 8 μm[2].

In addition to utilizing active devices, exploring the intrinsic nonlinearity of materials is also a significant research focus, as it can mitigate the need for photoelectric conversion to some extent.

In 2017, Cheng et al. reported the development of a hardware synapse implemented entirely in the optical domain through a photonic integrated-circuit approach (Figure 6c)[60]. Utilizing purely optical methods offers the advantages of ultrafast operation speed and virtually unlimited bandwidth and eliminates electrical interconnect power losses. The synapse employs phase-change materials in conjunction with integrated silicon nitride waveguides.

In 2024, Chen et al. developed an integrated nonlinear optical activator based on the butt-coupling integration of two-dimensional (2D) MoTe2 and optical waveguides (Figure 6d)[61]. The activator exhibits an ultra-broadband response from visible to near-infrared wavelength, a low activation threshold of 0.94 μW, a small device size (~50 μm[2]), an ultra-fast response rate (2.08 THz), and high-density integration. The excellent nonlinear effects and broadband response of 2D materials have been utilized to create all-optical nonlinear functions. These functions were applied to simulate MNIST handwritten digit recognition, achieving an accuracy of 97.6%.

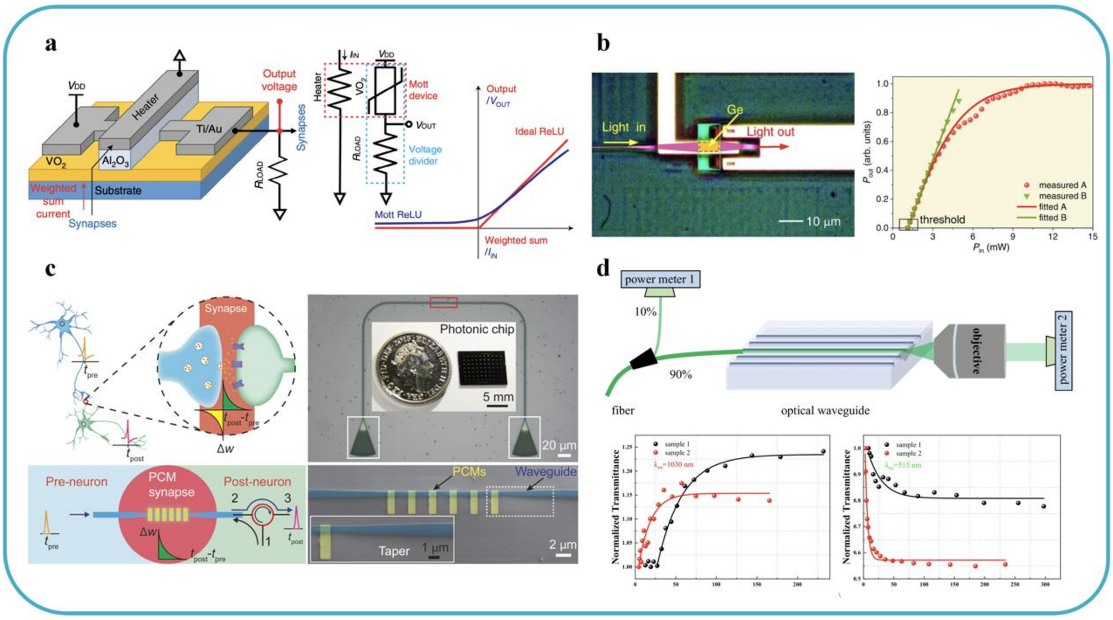

Figure 6. Nonlinear operators. a Mott activation neuron based on vanadium dioxide. b Nonlinear function based on germanium-silicon photodiodes. c On-chip photonic synapse based on PCMs. d Optical activator based on optical waveguides.

Fan-in and Fan-out

In large-scale integrated photonic computing systems, modulators and photodetectors (PDs) serve as critical electro-optic interfaces for data input and output. These devices enable efficient conversion between electrical and optical signals, facilitating precise optical signal processing in the photonic domain. In the context of optical computing, several key performance metrics are essential for evaluating modulators and photodetectors, including 3 dB bandwidth, data throughput, integration capacity, CMOS compatibility, and modulation efficiency. The capacity of modulators and PDs to achieve these performance benchmarks, along with their seamless integration into existing optical systems, is critical for facilitating the development of high-speed, scalable photonic circuits. This section provides an overview of recent advancements in modulator technologies, especially focusing on thin-film lithium niobate (TFLN) platforms, and explores their potential for integration into optical computing systems. By reviewing the current state of these technologies, we highlight the suitability for addressing the demands of large-scale photonic computing, emphasizing the ongoing efforts to improve their performance across these key metrics.

TFLN MZI Modulators

TFLN is often referred to as ‘optical silicon’ due to its prominent nonlinear electro-optic Pockels effect, which provides a significantly high electro-optic coefficient and enables highly efficient modulation performance. In addition to these material properties, TFLN significantly improves light confinement, integration, and compactness, resulting in high modulation efficiency[62]. These characteristics align with the performance metrics outlined later, positioning TFLN as the suitable material for modulators in large-scale PICs. Numerous miniaturized and high-performance TFLN modulators have already been demonstrated, further showcasing the platform’s potential.

Typically, TFLN modulators are designed using a MZI structure. In this configuration, modulation is achieved through the interference phenomenon caused by the phase difference between the two arms of the MZI modulator. These phase changes result in corresponding intensity changes, called Mach-Zehnder Modulator (MZM).

In 2018, Wang et al. proposed the first TFLN MZM in a traveling-wave MZI structure[63]. This design demonstrated a modulation efficiency of 2.2 V·cm and an electro-optic bandwidth of over 100

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GHz, while maintaining a CMOS-level voltage levels and supporting data rates beyond 200 G baud. This milestone represented a significant breakthrough in the development of TFLN-based integrated modulators (Figure 7a). Further, Feng et al. demonstrated an innovative application of a MZI structured TFLN modulator for medical image processing (Figure 7b) [64]. The TFLN MZM they used exhibits a 3dB bandwidth exceeding 67GHz while maintaining a modulation efficiency of 2.6V·cm. The researchers successfully implemented an optical image edge detection system within a deep convolutional neural network framework, achieving remarkable segmentation accuracy of 97.3% in their edge-enhanced computational model. This groundbreaking research not only showcases the potential of PICs in advanced computing applications but also establishes a significant foundation for the convergence of photonic technologies and artificial intelligence systems.

Subsequent progress on TFLN-based modulators has introduced a variety of advanced architectures. Examples include single-polarization In-phase & Quadrature (IQ) modulators[65], dual-polarization TFLN IQ modulators[66,67], and multi-loop design modulators[68]. For instance, Cai's group reported the first dual-polarization IQ (DP-IQ) modulator[67] (Figure 7c) which achieved a V_π of 1 V and an ultra-high 3-dB bandwidth of over 110 GHz for all sub-MZMs. Moreover, this DP-IQ modulator delivered a net bit rate of up to 1.96 Tb/s with ultra-low power consumption per bit (1.04 fJ/bit) at CMOS-level voltages. This work significantly advanced electro-optic interface speeds for integrated photonic computing systems while maintaining low power consumption.

Today, state-of-the-art TFLN MZMs have reached modulation efficiency of 0.21V·cm with a modulation bandwidth of surpassing 110GHz[69]. In other implementations, TFLN modulators exhibit a modulation efficiency of approximately 1 V·cm, 3-dB bandwidths surpassing 170 GHz[70], and insertion losses of only a few decibels[71].

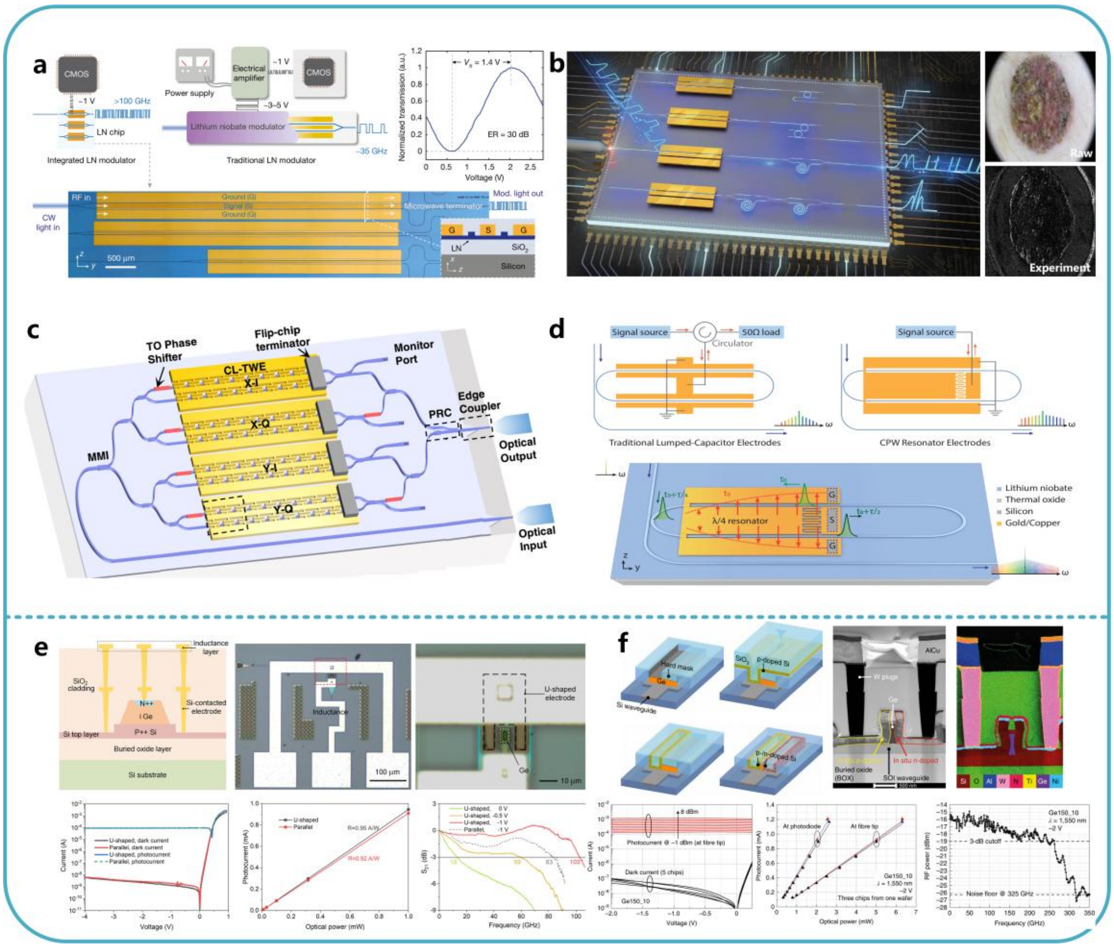

Figure 7. Typical high-speed electro-optical interfaces: modulators and photodetectors. a First MZI structure TFLN MZM. b First DP-IQ TFLN modulator. c Integrated lithium niobate microwave photonic processing

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engine. d A coplanar waveguide microwave resonator with an on-chip optical racetrack resonator TFLN modulator. e An optimized U-shaped electrode Ge-Si PD. f An ultra-high bandwidth of 260 GHz PD.

TFLN cavity-based modulators.

In pursuit of minimizing the spatial occupation of modulators on integrated circuits, enhancing EO modulation efficiency, suppressing RF losses in MZI modulators and ensuring precise velocity matching, cavity-based modulators have emerged as a critical paradigm in the field of optical modulation technology. These devices often integrate a ring waveguide with an applied electric field, employing configurations such as photonic crystal cavities[72], ring cavities[73], Fabry-Perot (FP) cavities[74], and Bragg grating resonator cavities[75], all of which are engineered to confine photons for extended durations. Owing to the structural constraints inherent in cavity design, a fundamental trade-off exists between the bandwidth and quality factor (Q) in these modulators. As a representative example, Wang et al.[76] proposed a novel architecture that synergistically combines a coplanar waveguide microwave resonator electrode with an on-chip optical racetrack resonator, demonstrating significant performance enhancements (Figure 7d). This optimized configuration demonstrates significant performance metrics, achieving a quality factor (Q factor) of 8.5×10^5 through implementation of a 2.3 mm racetrack resonator. The device successfully generates broadband optical frequency combs (OFCs) with a spectral coverage exceeding 85 nm, while maintaining a free spectral range (FSR) of approximately 25 GHz, which corresponds to the microwave driving frequency. These experimental results substantiate the viability of this approach as a practical and economically favorable solution for developing high-performance integrated electro-optic frequency comb generators in photonic integrated circuits.

Beyond TFLN modulators, a variety of other materials have been demonstrated on the silicon photonics platform, including pure silicon modulators[77,78], silicon-based thin-film lithium tantalate modulators[79], silicon-based germanium modulators[80,81], and silicon-based polymer hybrid modulators[82,83]. For example, an advanced slow-light silicon modulator has achieved an impressive bandwidth of 110 GHz, supporting a data rate of 112 Gbps within an 8 nm spectral window for on-off keying (OOK) signals[77]. Pure silicon modulators are particularly well-suited for large-scale, cost-effective photonic chips due to the maturity of CMOS fabrication technology. While silicon's centrosymmetric crystal structure inherently limits its nonlinear electro-optic properties, ongoing research continues to explore alternative approaches to enhance modulation capabilities within silicon photonic platforms.

Photodetector

In programmable photonic circuits composed of large arrays of MZI or MRR, PD primarily serve to convert optical signals into electrical signals[84,85]. Moreover, in certain convolutional computing operations, PDs also perform summation functions across multiple convolutional kernels[6,86]. As the demand for increased speed and data throughput continues to rise, striking an optimal balance between bandwidth, internal responsivity, and sensitivity for PDs becomes an increasingly pressing challenge.

In recent years, significant advancements in low-power optical signals in fibre optic communication, sensing biotechnologies and quantum applications have driven the development of high-speed and high sensitivity PDs[87], which have progressively matured with improvements in material quality and processing technologies. Based on the photoactive materials used, PDs can be categorized into those employing III-V compounds, such as InGaAs[88], HgCdTe[89,90]and InP[91], AlInAsSb[92], emerging two-dimensional (2D) materials, including graphene[93], perovskites[94] and germanium[95–97].

Therein, germanium-on-silicon (GeSi) technology has advanced rapidly, achieving high compatibility and maturity in integrated photonic applications. For instance, Zhang et al. demonstrated a breakthrough by achieving a bandwidth exceeding 100 GHz with vertically integrated germanium photodetectors, along with an impressive optical responsivity of 0.95 A/W. Additionally, their work successfully realized open eye diagrams for 120 Gbps on-off keying (OOK)

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and 200 Gbps four-level pulse amplitude modulation (PAM-4) signal transmission[98]. This work offers a promising solution for ultra-fast photodetection on chip (Figure 7e). In addition, L. Zimmermann et al. achieved a remarkable breakthrough in photodetector bandwidth, demonstrating an ultrahigh 3 dB bandwidth of 265 GHz on a silicon waveguide-coupled germanium structure [99] (Figure 7f). While the internal responsivity of the device at 1550 nm is limited to 0.3 A/W, highlighting a trade-off between bandwidth performance and responsivity. Broadly speaking, the large bandwidth, high sensitivity and nice internal responsivity PD still needs a long way to go on the manufacture and technologies.

Table 1. Performance comparison of modulator across various architectures or material platforms.

Ref.	**Platform**	**Structure**	**Bandwidth-3dB (GHz)**	**physical size**	**Vπ**	**Signal rate**
63	TFLN	MZM	45GHz	20mm	1.4V	210Gbit/s 8-ASK
63	TFLN	MZM	100GHz	5mm	4.4V	200Gbaud
67	TFLN	DPIQ	110GHz	23.5mm	1V	1.96Tb/s 400QAM
69	TFLN	MZM	110GHz	1mm	2.1V	N.A.
100	TFLN	Folded MZM	>67GHz	22.5mm	1V	703Gb/s
101	TFLN	Micro-structured electro	>100GHz	N.A.	1.3V	N.A.
72	TFLN	EOM resonator	17.5GHz	~0.58um^3	N.A.	12Gb/s
77	Si	Bragg grating	110GHz	0.124mm	5V	112Gb/s
80	SiGe	MZM	43GHz	500mm	3.8V	128Gb/s

Large-scale on-chip photonic neural networks

In the domain of photonic neural networks, enhancing computational performance, enabling large-scale photonic computing, and optimizing energy efficiency are essential objectives. To meet these demands, a key strategy is the integration of heterogeneous components onto a monolithic chip. Furthermore, the deployment of multi-layer neural network architectures within a single chip is critical for realizing scalable and efficient photonic computing solutions. Recently, there has been a considerable amount of research focused on achieving this goal.

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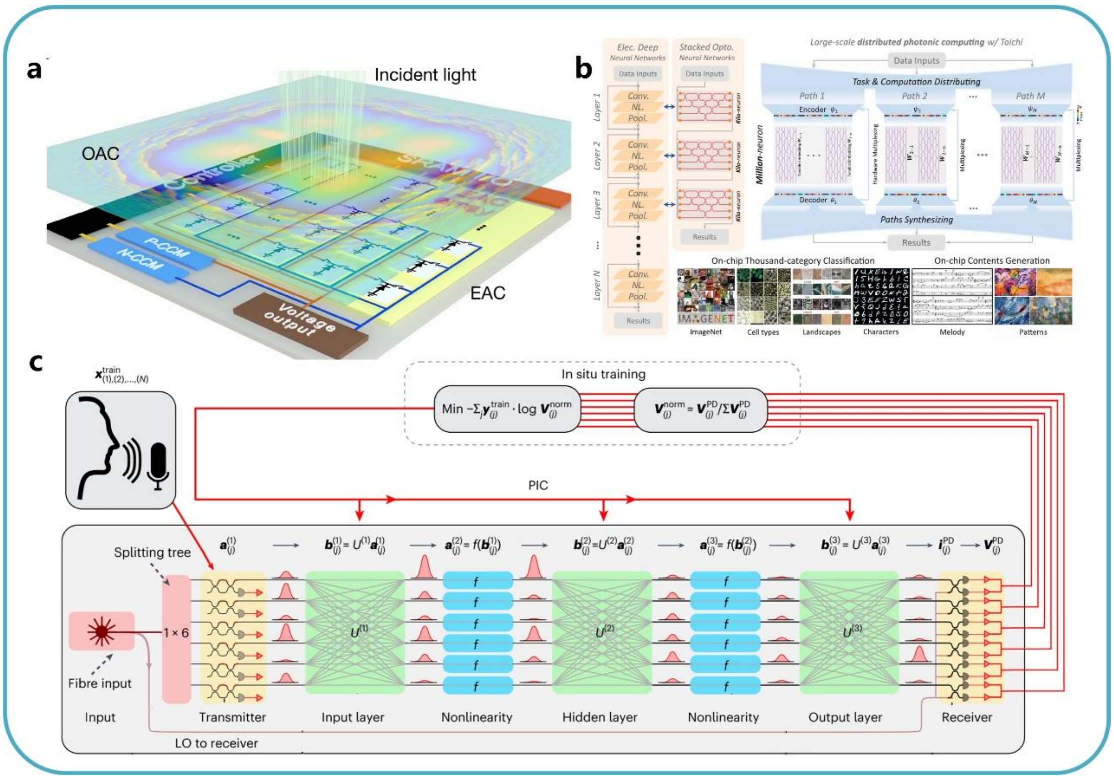

Figure 8. Large scale PNNs. a ACCEL. b Taichi. c Single-chip PNN.

For example, Dai's group introduced ACCEL[103], an all-analog chip combining diffractive optical and electronic analog computing, achieving on-chip scalability, nonlinearity, and flexibility (Figure 8a). By encoding information directly into light fields and using photodetectors for nonlinear operations, ACCEL achieved 97.1% accuracy on 10-class MNIST, offering a promising framework for intelligent computing. The following year, the same group developed Taichi[18], a large-scale photonic chiplet platform with a diffractive-interference hybrid design (Figure 8b). Taichi excelled in complex tasks like 1000-category classification, advancing photonic computing for artificial general intelligence (AGI) applications.

In 2024, MIT achieved a breakthrough with the fully monolithic integration of coherent optical neural networks[102], combining a coherent matrix multiplication unit and optical nonlinear function unit on a single chip as shown in Figure 8c. Fabricated using a commercial silicon photonics process, the chip integrates programmable linear and nonlinear transformations, enabling in-situ training, nanosecond latency, and femtojoule efficiency. This advancement achieved 92.5% accuracy on vowel classification, marking a significant step toward scalable and efficient optical computing.

Additionally, we have compiled a comprehensive summary of recent advancements in integrated ONNs in Table 2, highlighting key developments in power consumption, computational speed, and integration density over the past few years.

Table 2. Comparison of state-of-the-art integrated photonic neural network systems.

Ref.	Integration Level	Integrated Devices	Computing Speed (TOPS)	Power (TOPS/W)	Materials	Tasks	Latency	Footprint (mm[2])
102	End-to-end DNN	MZM PD MZI MRR	0.59	0.013	SiP	Six-class vowel classification (92.5%)	410ps	34.2
42	End-to-end PDNN	PIN PD MZM	0.27	0.07	SiP SiGe	Two-class classification (93.8%)	0.57 ns/frame	9.3

31	Linear unit light source	MRR PCM	4	0.4	Si_3N_4 $Ge_2Sb_2Te_5$	MNIST (95.3%)	8.1×10^3 ns/ frame	~6.5
103	Linear unit Nonlinear unit	Phase mask PD	4.55×10[3]	7.48×10[4]	SiO_2	Time-lapse video recognition (92.6%)	72 ns	4.7
18	Input Output Linear unit	Diff. units PS MZI VOA	5×10[4]	160.82	Si TiN	1623-category Omniglot dataset (91.8%)	3.79 ms	N.A.
25	Light source Linear unit	OFC MRR	51.2	4.18	Si_3N_4	Human emotion recognition (78.5%)	N.A.	~5
104	Light source Output Linear unit	LED PD gratings	N.A.	N.A.	perovskit e Si_3N_4	Edge detection (85%)	N.A.	~5
22	Light source Input Linear unit	OFC EOM MRR DL	0.136	0.2	SiP AlGaAs	Edge detection (96.9%)	58.88ps	0.131

Outlook/Discussion

PNNs based on PICs have significantly improved in the areas discussed above. Notably, substantial progress has been achieved in implementing linear operators, with various architectures leveraging different optical devices. Photonics offers distinct advantages in computational speed and energy efficiency, and it has demonstrated substantial industrial relevance. The computing speed of linear operators typically reaches the trillions of operations per second (TOPS) level. In certain specialized diffractive metasurfaces, even peta-operations per second (POPS) can be achieved. Furthermore, as optical material platforms continue to mature, a wide range of active optical devices—such as modulators, photodetectors, and lasers—can now facilitate input/output (I/O) operations and nonlinear functions. Despite these advancements, several challenges persist.

a) Multi-linear layers based on integrated photonic circuits

Currently, the implementation of linear operators based on PICs has attained a level of maturity, with most works showcasing a single layer of linear operations in the optical domain. However, multiple layers of linear operators are crucial for facilitating complex AI tasks and deep neural networks. Therefore, there is a necessity to further enhance the integration of PICs in the future, fully leveraging the benefits of optical linear computations to enable multi-layer operations that can address more intricate challenges.

b) Implementing all-optical nonlinear operators

Implementing optical nonlinear operators remains predominantly at the research stage. The mainstream architecture of PNNs employs a hybrid photoelectric computing approach, in which linear computations are executed in the optical domain while nonlinear operations are performed in the electrical domain. However, due to limitations such as photoelectric rate mismatches and additional energy consumption, this approach fails to fully exploit optical computing's advantages.

c) Monolithic integrated photonic networks

A conventional neural network consists of an input layer, an output layer, linear operators (weight matrices), and nonlinear operators (activation functions). Implementing these functions within the photonic domain requires the integration of lasers, passive components, and active components to establish a fully functional computing system. However, due to the limitations of material characteristics and integrated processing technology, most works integrated only partial

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functions within the optical domain or leveraged different material platforms to develop specialized devices.

Various integrated photonics technologies have been developed to address these challenges, with minimizing optical waveguide loss being a fundamental prerequisite for achieving large-scale integration. Hence various low-loss optical waveguides have been proposed on different materials, including Si_3N_4, SiO_2, and silicon[105–108]. The lowest loss has reached approximately 0.1 dB/cm. In addition, emerging material platforms such as graphene, MoS_2, and WS_2 hold great potential for enabling disruptive advancements in nonlinear and active photonic devices[109,110]. Heterogeneous integration has emerged as the most promising strategy to fully leverage the advantages of diverse material platforms and ultimately realize monolithic PNNs, as demonstrated in Figure 9 [111–113]. Overall, integrated photonics technology is shaping the present and future of PNNs, paving the way for more efficient and scalable optical computing architectures.

These results confirm the effectiveness of optical microcombs in forming the basis for transversal filter microwave spectral filters [114–128] potentially involving advanced circuit designs [136–195] including graphene oxide and other 2D material based devices, [174–203] with applications to quantum optics. [190–241]

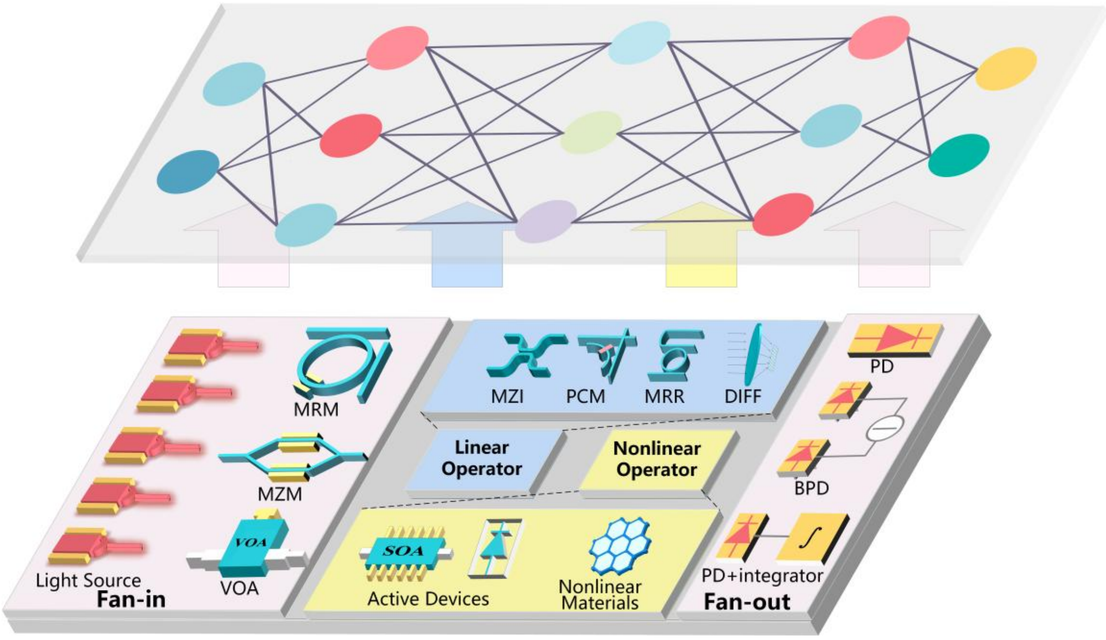

Figure 9. Schematic of monolithically integrated PNNs.

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