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To cite this article: Hyo-Bin Jang *et al* 2026 *Nano Futures* **10** 032502

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## PERSPECTIVE

## Toward optically programmable crossbar arrays for array-level artificial neural network hardware

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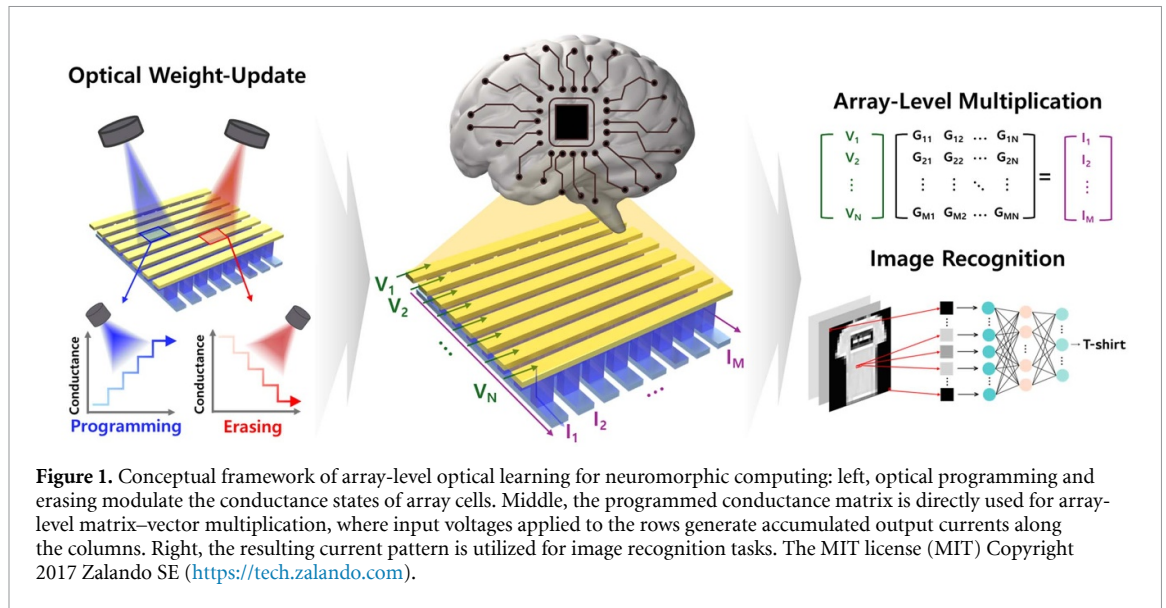
E-mail: [twlees@snu.ac.kr](mailto:twlees@snu.ac.kr) and [parkhl21@seoultech.ac.kr](mailto:parkhl21@seoultech.ac.kr)**Keywords:** neuromorphic computing, artificial neural networks, optical synaptic devices, optical conductance modulation, array-level learning**Abstract**

Neuromorphic computing has attracted considerable attention as an efficient approach to overcoming the limitations of conventional von Neumann architectures. For the practical hardware implementation of artificial neural networks (ANNs), device operation should extend beyond individual cells to array-level architectures, typically realized as crossbar arrays in which synaptic weights are stored as the conductance states of individual cells and directly utilized for matrix–vector multiplication (MVM). In this context, crossbar arrays serve not only as high-density integration platforms but also as core computing architectures in which stored conductance distributions are directly utilized for MVM. However, conventional electrically modulated arrays often suffer from unintended disturbances through shared interconnects during programming and erasing, thereby limiting computational reliability. As a promising alternative, optically modulated systems enable selective and parallel weight control in a non-contact manner. Realizing these advantages in practical computing, however, requires optical learning to be implemented at the array level. In this Perspective, we review optically programmable crossbar arrays from the perspective of array-level ANN implementation. We first discuss the key mechanisms governing optical programming and erasing, and then examine the major requirements for array-level optical learning, including update uniformity, reliability, and efficiency. Finally, we highlight current progress, remaining challenges, and future perspectives toward the realization of optically programmable crossbar array-based ANN hardware.

**1. Introduction**

Recent advances in artificial intelligence have intensified the demand for computing platforms capable of processing large volumes of real-time data at high speed and with high energy efficiency [1, 2]. However, conventional digital electronic systems, such as graphics processing units and tensor processing units, retain physically separate memory and computation units, requiring repeated transfer of weights through the memory hierarchy and thereby incurring latency and energy overheads [3–6]. These limitations have driven growing interest in alternative computing architectures that can overcome the structural constraints of conventional von Neumann systems [7, 8].

Neuromorphic systems inspired by biological neural networks have attracted considerable attention as promising candidates for next-generation computing platforms [9–12]. In biological neural networks, memory storage and signal processing occur concurrently, thereby enabling highly parallel and energy-efficient computation [13, 14]. To implement this operational principle in hardware artificial



neural network (ANN) systems, devices should be configured in array formats rather than operated individually [15–17]. Among various hardware architectures, crossbar arrays have attracted particular interest because synaptic weights are stored as the conductance states of individual cells, while matrix–vector multiplication (MVM) is performed directly within the same physical array. When input voltages are applied simultaneously to the rows, each cell performs multiplication according to Ohm’s law, and the resulting output currents are accumulated along the columns according to Kirchhoff’s current law [18]. This in-memory operation reduces repeated weight transfer and enables highly parallel analog MVM. By contrast, in many current optical and photonic neural network (ONN/PNN) architectures, the memory elements that maintain the synaptic weights are physically separated from the optical processing unit that performs MVM. Thus, unlike crossbar arrays, in which the stored conductance states directly participate in MVM within the same physical array, memory and computation remain separated at the system level in many ONN/PNN implementations, requiring additional interfaces between functional components and thereby increasing overall system complexity. Therefore, to fully realize these architectural advantages, practical crossbar array-based ANN hardware systems require a precise and reliable array-level weight-update scheme that can accurately establish the target conductance distribution [19, 20].

However, satisfying this requirement remains challenging with conventional electrical programming and erasing schemes. At the array level, electrical weight-updating suffers from two major limitations: the update process becomes progressively inefficient as the array size increases, and the target conductance distribution across the array is difficult to establish with high precision [21–23]. This is because the conductance of each cell in crossbar arrays is generally adjusted through serial, cell-by-cell programming and erasing, which inherently constrains update efficiency in large-scale arrays [24–26]. In addition, during electrical updating, part of the applied bias can affect unselected cells even though they are not intended to be modified [27–29]. Such unintended electrical stress can perturb their stored conductance states, thereby compromising the precision and reproducibility of array-level weight-updating [30, 31]. Accordingly, optical conductance modulation has emerged as a promising strategy for array-level weight control [32–34]. Because light can be spatially focused and selectively delivered to desired cells or regions, it can enhance update selectivity while suppressing electric-field-induced conductance disturbances in unselected cells [35–37]. Furthermore, the spatial selectivity of light enables parallel updating of multiple cells or regions simultaneously [38]. These characteristics make optical learning particularly attractive for rapid weight-updating in large-scale crossbar arrays.

Previous studies on optically modulated devices have largely concentrated on demonstrating light-induced conductance modulation at the individual-device level and elucidating the associated mechanisms [39]. Consequently, array-level requirements pertinent to practical ANN hardware have received relatively limited attention in existing reviews. From this standpoint, the present perspective addresses optically modulated devices specifically in the context of array-level ANN implementation (figure 1). We first categorize optically modulated devices into unidirectional and bidirectional optical modulation schemes according to the extent of light involvement in the weight-update processes. We then discuss the key requirements for array-level optical modulation and examine representative

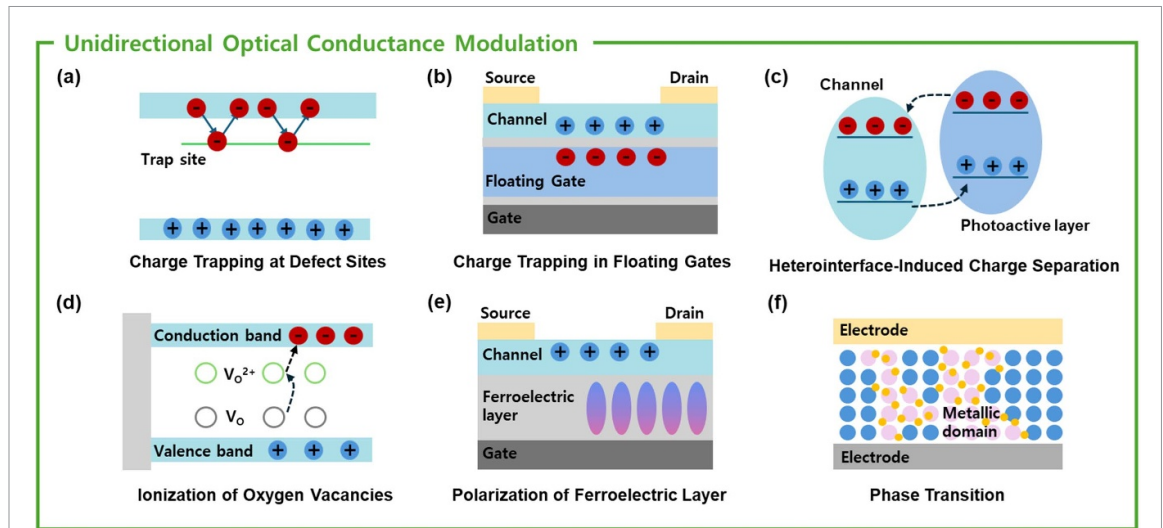


**Figure 2.** Schematic illustrations of representative mechanisms for unidirectional optical conductance modulation include (a) charge trapping at defect sites, (b) charge trapping in floating gates, (c) heterointerface-induced carrier separation, (d) ionization of oxygen vacancies, (e) polarization of ferroelectric layer, and (f) phase transition.

demonstrations in which optical weight-updating is incorporated into array-level ANN operation. Finally, we discuss the remaining challenges and future directions for translating proof-of-concept demonstrations of optically programmable devices into scalable crossbar arrays for practical ANN hardware implementation.

## 2. Mechanisms for optical weight modulation

Weight modulation includes a programming process that sets the conductance of a cell to a desired value and an erasing process that returns the programmed conductance to its initial state [40–42]. In optically modulated ANN systems, these operations can be categorized into two types depending on the extent to which light is involved. One is unidirectional optical modulation, in which light participates in only one of the programming or erasing processes, whereas the other is bidirectional optical modulation, in which both processes are performed solely by light. Because the conductance of each cell serves as a synaptic weight in ANN operation, the optically modulated conductance state should remain sufficiently stable after modulation. Accordingly, this section discusses the mechanisms underlying these two schemes, focusing on how optically modulated conductance states are established and maintained as reliable weight levels for ANN operation.

### 2.1. Unidirectional optical modulation mechanism

Unidirectional optical modulation refers to a conductance-update scheme in which light participates in either programming or erasing, while the reverse process is achieved by a non-optical stimulus. The optically driven process can reduce unintended disturbances in unselected cells; however, because conductance modulation in the opposite direction is typically performed electrically, such disturbances are not completely eliminated in array architectures. Despite this operational limitation, unidirectional optical modulation can be implemented using a single-photoactive-layer-based structure, offering advantages in structural simplicity and ease of fabrication.

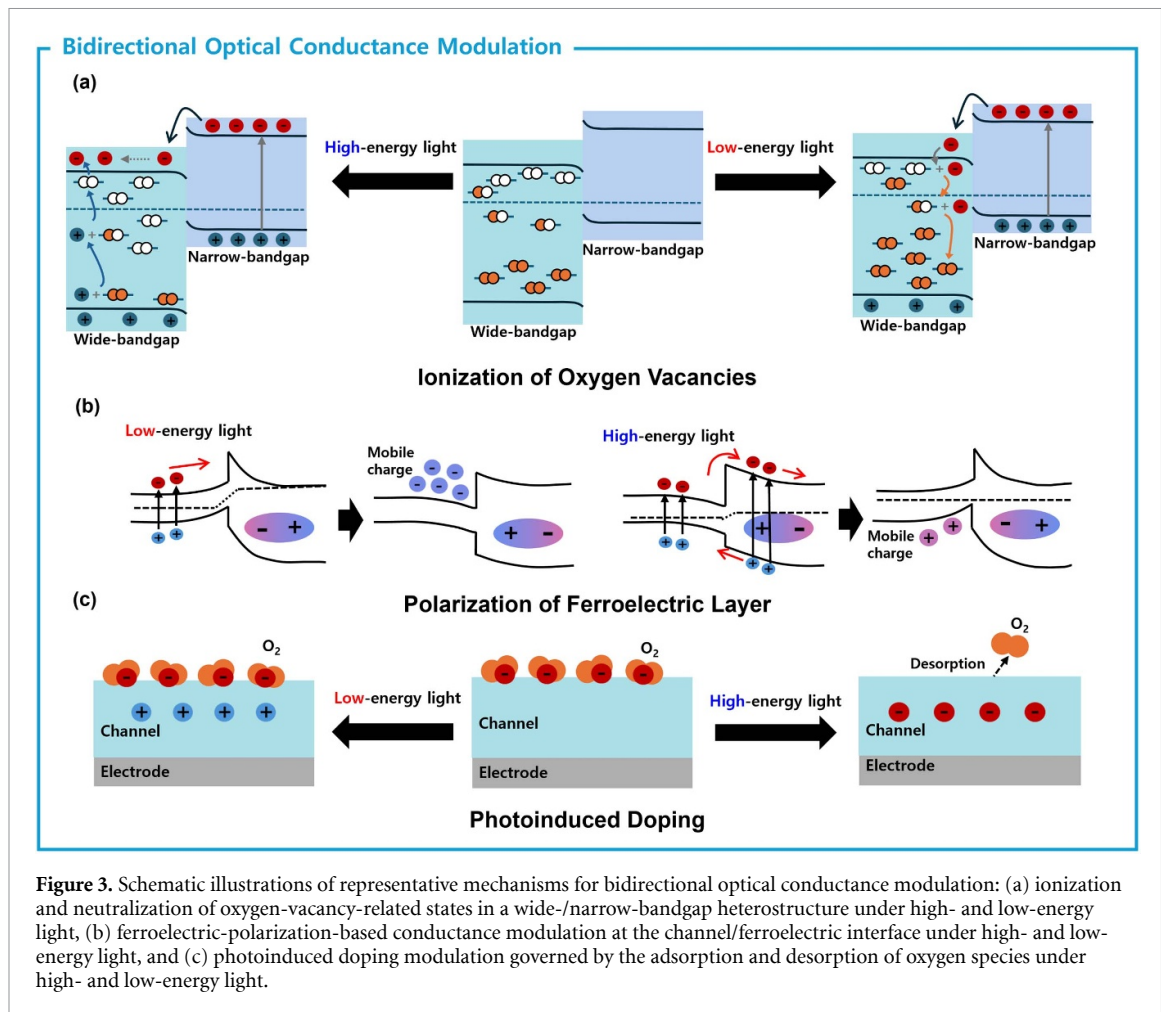
Charge trapping, a representative mechanism for regulating the effective carrier concentration in the channel, can originate from defect-related trap states or interfacial potential wells arising from different band-alignment between two materials, as illustrated in figure 2(a) [43–45]. When light is incident on the photoactive layer, photogenerated electron–hole pairs within the photoactive layer are separated, after which a portion of the carriers migrates to trap sites and becomes captured [46–48]. This process suppresses recombination and alters the effective carrier concentration in the channel, resulting in a corresponding conductance change. In many organic materials (e.g. C8-BTBT and pentacene) and oxide materials (e.g. InGaO and ZnO), dangling bonds generated by structural discontinuities at the interface between the dielectric and the photoactive layer can act as trapping centers for photogenerated carriers [49]. In low-dimensional materials with a high surface-to-volume ratio, such as MoS<sub>2</sub> and ReS<sub>2</sub>, defect-induced surface trapping can dominate charge transport and recombination

behavior. Floating-gate-based conductance modulation, in which materials such as CsPbBr<sub>3</sub> quantum dots (QDs) and carbon nitride (C<sub>3</sub>N<sub>4</sub>) serve as floating-gate layers, is achieved using a device structure in which an isolated floating-gate layer is inserted between the channel and the gate insulator, as shown in figure 2(b). In such devices, optical modulation can be described by two representative charge-transfer pathways, depending on the location of photocarrier generation and the direction of carrier transfer. In the first pathway, photogenerated carriers in the photoactive channel layer tunnel through the tunneling layer and are trapped or stored in the floating-gate layer. In the second pathway, photocarriers generated in the floating-gate layer tunnel through the tunneling layer and are injected into the channel layer. Although the direction of charge transfer differs between these two pathways, both processes generate stored or spatially separated charges in the vicinity of the channel/floating-gate stack. These charges are not readily recombined after illumination because they are confined in the floating-gate layer or separated across the tunneling layer. The resulting electrostatic potential shift modulates the effective carrier concentration in the channel, leading to a persistent change in device conductance even after the optical stimulus is removed [50, 51]. Although the photoactive layer is typically used as the channel, an alternative approach employs different materials for the channel and the photoactive layer to form a junction, thereby leveraging potential wells arising from band-alignment offsets such as amorphous indium–gallium–zinc oxide (*a*-IGZO)/MoS<sub>2</sub> heterostructure, where *a*-IGZO serves as the channel and MoS<sub>2</sub> functions as the photoactive layer, or a MoS<sub>2</sub>/3,4,9,10-perylenetetracarboxylic dianhydride (PTCDA) heterostructure, where MoS<sub>2</sub> serves as the channel and PTCDA acts as the photoactive layer [52]. As shown in figure 2(c), under illumination, some photogenerated charges in the photoactive layer transfer to the channel layer, where they are trapped by the interfacial energy-level offset, thereby suppressing recombination. Consequently, the carrier density in the channel is modulated, leading to a corresponding change in conductance [53].

Another reported mechanism for conductance modulation in metal-oxide-based devices, such as IGZO, indium oxide (In<sub>2</sub>O<sub>3</sub>), and indium zinc oxide (IZO), is the photoinduced ionization of oxygen vacancies, as illustrated in figure 2(d) [54]. Under illumination, neutral oxygen vacancies become ionized and release free electrons, increasing the electron concentration in the channel and thereby enhancing the conductance. Because these vacancies do not immediately neutralize due to a large activation-energy barrier, the conductance does not rapidly decay after the light is turned off, enabling memory behavior. Oxide semiconductors such as IGZO, In<sub>2</sub>O<sub>3</sub>, and IZO are considered promising material platforms for complementary metal–oxide–semiconductor (CMOS)-oriented integration because they combine relatively low-temperature deposition with scalable large-area fabrication. Many oxide semiconductors can be prepared in an amorphous form, thereby avoiding grain-boundary-related nonuniformity and facilitating relatively uniform electrical characteristics across large-area arrays [55]. Moreover, their compatibility with established deposition techniques, including sputtering and atomic layer deposition (ALD), has enabled wafer-scale fabrication and monolithic three-dimensional integration demonstrations [56].

Another mechanism for modulating the carrier concentration in the channel is polarization-based conductance modulation, in which ferroelectric materials, such as poly(vinylidene fluoride-trifluoroethylene) (P(VDF-TrFE)), hafnium zirconium oxide (HZO), and aluminum scandium nitride (AlScN), are employed as the polarization layer (figure 2(e)) [57]. The suitability of ferroelectric materials for CMOS integration strongly depends on the material and fabrication. In this context, HZO and AlScN have attracted particular attention as emerging platforms because they can be deposited using established thin-film fabrication techniques. HZO can be deposited by ALD or sputtering, scaled to ultrathin film thicknesses, and crystallized within thermal budgets of approximately 400 °C in back-end-of-line-compatible device demonstrations [58, 59]. AlScN can likewise be deposited by reactive sputtering and has been incorporated into optoelectronic ferroelectric devices fabricated within silicon BEOL-compatible process windows, making it another promising candidate for CMOS-integrated optoelectronic devices [60]. When light is incident on an active layer formed on a ferroelectric layer, electron–hole pairs are generated, and some of them drift toward and accumulate near the interface due to the polarization-induced bound charges. The accumulated photoinduced charges generate an additional internal electric field in the active layer, thereby altering the carrier density in the channel and inducing a corresponding change in conductance.

As illustrated in figure 2(f), phase transition provides another mechanism for conductance modulation. Under high-energy illumination, electron–hole pairs are generated in the high-valence metal oxide film (e.g. vanadium dioxide (VO<sub>2</sub>)), and the photogenerated electrons are promoted to the conduction band [61]. Meanwhile, photogenerated holes react with adsorbed water molecules to produce protons. These photogenerated electrons and protons cooperatively reduce the valence state of the metal ions from a higher to a lower oxidation state, which can lead to the formation of a hydrogenated bronze



phase. This process reconstructs the dominant conduction pathway and induces a transition in the resistive state.

## 2.2. Bidirectional optical modulation mechanism

Bidirectional optical modulation relies on wavelength-dependent photoresponses to induce opposite conductance changes for programming and erasing. This behavior can be realized by controlling the interfacial barrier through the built-in potential of a heterojunction formed between different photoactive materials. Another approach employs a single photoactive layer, in which the doping level is modulated in a wavelength-dependent manner to increase or decrease the carrier concentration depending on the illumination wavelength.

As illustrated in figure 3(a), one representative strategy for implementing bidirectional conductance modulation through an interfacial barrier is to design a heterojunction composed of two materials with different bandgaps, such as pyrenyl graphdiyne/graphene/PbS QDs, IGZO/SnO/SnS, and  $\text{In}_2\text{O}_3$ /PBDB-T-2 F [62]. In general, a metal oxide is used as the layer with the relatively wider bandgap material. Under high-energy illumination, oxygen-vacancy-related defect states in the wide-bandgap metal oxide are ionized, releasing additional free electrons and thereby increasing the conductance [63]. Photogenerated carriers are also generated in the relatively narrow-bandgap layer, and some of them acquire additional energy under high-energy illumination and are subsequently transferred to the metal oxide layer, where they contribute to charge transport [64]. As a result, the electron concentration in the channel increases under high-energy illumination, enabling a programming process. In contrast, under low-energy illumination, selective photoexcitation occurs only in the relatively narrow-bandgap layer. Rather than being transported as current, the generated charges contribute to neutralizing the ionized oxygen vacancies in the metal oxide [65]. Accordingly, the additional electrons that had increased due to oxygen-vacancy ionization are reduced, and the charge concentration in the channel returns to its original level. As a result, an erasing process is achieved under low-energy illumination. Another interfacial-barrier-based mechanism determines conductance modulation through the band alignment formed at the channel/ferroelectric interface and the polarization state of the ferroelectric

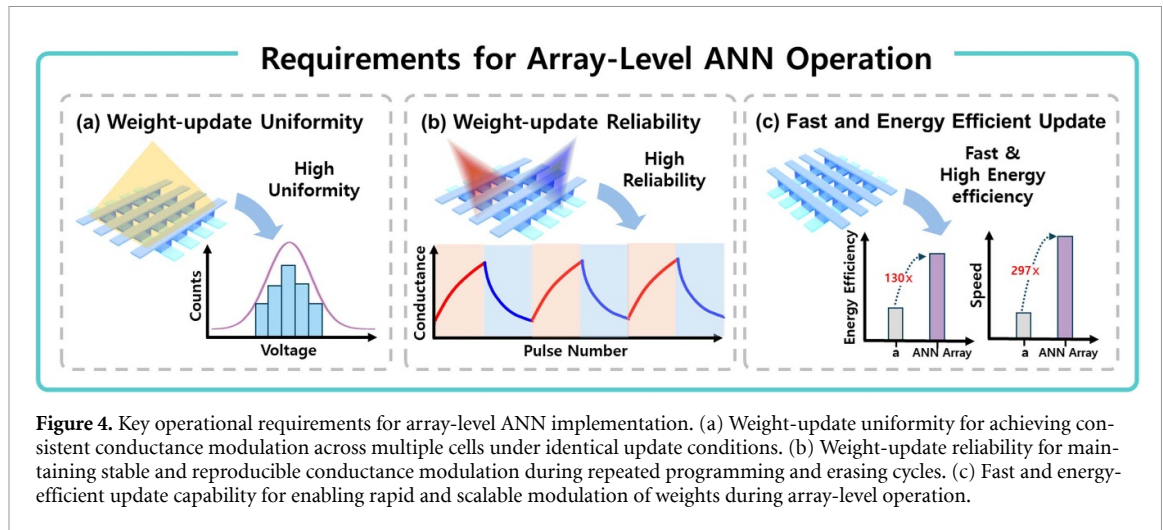
layer, as described in figure 3(b). Materials with this behavior include organic semiconductor/P(VDF-TrFE) and CuPc/P(VDF-TrFE) heterostructures. When the channel layer is interfaced with the ferroelectric layer, this built-in potential is formed and can induce the polarization of the ferroelectric layer to align in a specific direction [66]. Under these conditions, in which the interfacial potential and polarization state are established, different charge behaviors can arise depending on the illumination energy. In general, the channel has a narrower bandgap than the ferroelectric layer. Therefore, under low-energy illumination, optical absorption occurs primarily and selectively in the channel, and photogenerated carriers are also formed mainly in the channel. Although low-energy illumination generates photocarriers, it does not provide sufficient energy for them to surmount the interfacial barrier. As a result, the generated photocarriers cannot cross the interfacial barrier formed between the channel and the ferroelectric layer and instead accumulate near the interface. The electrons accumulated near the interface create a local electric field, thereby inducing the pre-existing polarization of the ferroelectric layer to reorient into a specific direction. The resulting polarization state continues to act as an effective electric field on the channel even after the illumination is removed, thereby maintaining electron accumulation near the interface and sustaining an increased effective electron concentration in the channel. Accordingly, under low-energy illumination, interfacial electron accumulation, ferroelectric polarization alignment, and an increase in channel electron concentration are sequentially linked, ultimately giving rise to programming behavior with increased conductance [67, 68]. In contrast, under high-energy illumination, photocarriers are generated not only in the channel but also within the ferroelectric layer. Unlike under low-energy illumination, high-energy illumination provides sufficient additional energy for the photocarriers generated in the channel to surmount the interfacial barrier. As a result, the electrons that had accumulated near the interface under low-energy illumination move across the interface, and the previously formed interfacial electron accumulation is relaxed. Accordingly, the polarization alignment of the ferroelectric layer induced by charge accumulation returns to its original direction, and the effective electron concentration in the channel also recovers to its initial level. Consequently, an erasing process that restores the conductance toward its original level can be achieved under high-energy illumination. Another approach involves a photoinduced doping modulation mechanism that enables bidirectional optical modulation using a single photoactive layer (figure 3(c)), as demonstrated in materials such as PdSe<sub>2</sub> and SnSe. This mechanism is typically observed in p-type low-dimensional materials, where strong-electronegativity adsorbates such as moisture or oxygen molecules induce p-type doping at the surface [69]. Under low-energy illumination, adsorption of oxygen molecules is preferentially maintained at the surface. Specifically, oxygen molecules are adsorbed on the surface and capture electrons owing to their strong electronegativity, thereby forming superoxide ions (O<sup>2-</sup>). This electron trapping increases the hole concentration and gives rise to a p-type doping effect in the channel. Although low-energy illumination can generate photocarriers, it does not provide sufficient energy to neutralize the adsorbed oxygen ions and induce their desorption. Therefore, the adsorbed oxygen ions remain on the surface, while conductance enhancement occurs through the photogenerated carriers. Such low-energy illumination consequently leads to a programming process that increases the conductance. In contrast, under high-energy illumination, photocarriers are generated and the adsorbed oxygen ions on the surface are neutralized, causing the adsorbed O<sup>2-</sup> species to desorb and be released back into the gas phase. Because this desorption process removes oxygen molecules that act as electron acceptors at the surface, the electron concentration in the channel increases and the hole concentration correspondingly decreases. As a result, the conductance decreases, thereby enabling an erasing process.

### 3. Optical programming at the array-level for neuromorphic computing

#### 3.1. Requirements for array-level ANN operation

For ANN implementation, weight modulation should be considered at the array level, where programming and erasing should precisely establish the target conductance distribution across the array [70]. Key considerations include how uniformly a given programming or erasing update condition is reflected across multiple cells, how well the states of previously programmed cells are preserved while selected cells are being updated, and how rapidly and efficiently large-scale weight-updating can be carried out.

Weight-update uniformity refers to the extent to which an identical programming or erasing process produces consistent conductance changes across multiple cells (figure 4(a)). This is a critical requirement for efficiently implementing a target weight distribution in large-area arrays without adjusting the update conditions for individual cells. In conventional electrical weight-update schemes, intrinsic device-to-device variation and position-dependent voltage drops during update can each cause the conductance



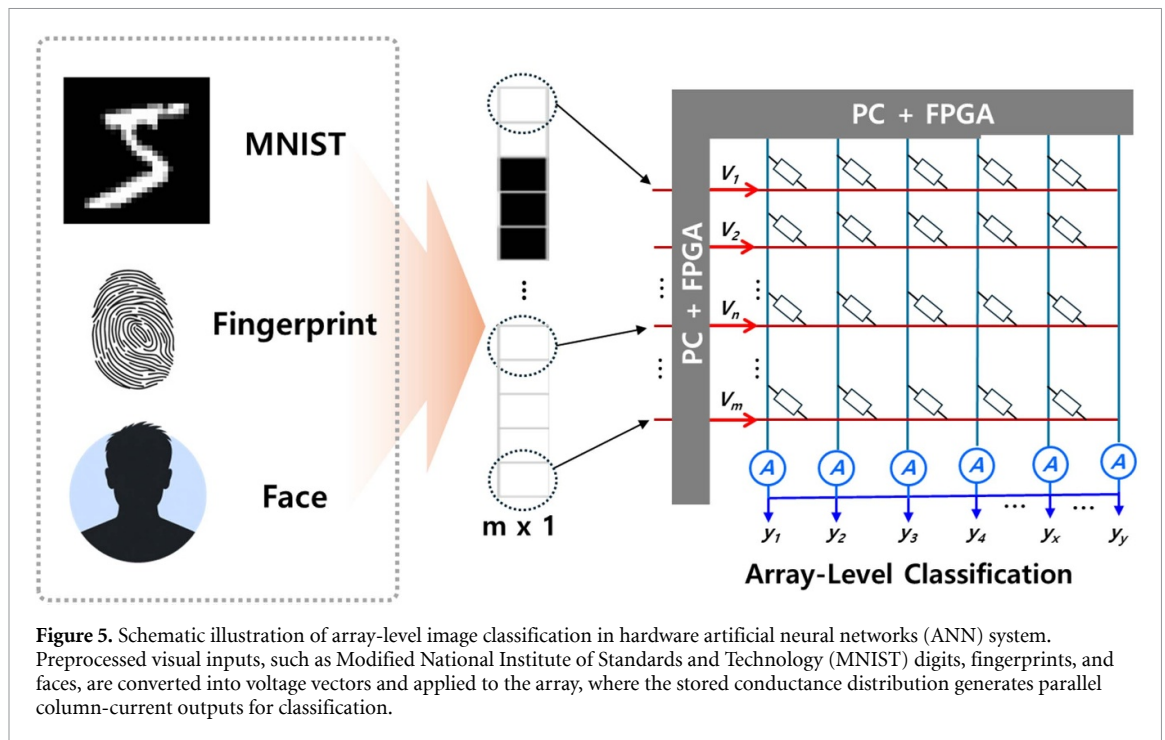
states of individual cells to deviate from their intended values even under identical applied conditions [71, 72]. From this perspective, optical conductance modulation is particularly valuable because it enables more uniform weight-updating during repeated array-level update operations.

Weight-update reliability refers to how well the states of previously programmed cells are preserved while selected cells are being updated as illustrated in figure 4(b). In array-based ANN systems, this requirement becomes particularly important because learning involves repeated updates across large numbers of cells [73, 74]. During electrical updating, unintended bias on unselected cells can perturb stored conductance states and progressively distort the programmed weight distribution [75]. From this perspective, optical conductance modulation is advantageous because optical stimuli can be confined to selected cells or defined regions through laser scanning or mask-assisted illumination, thereby reducing disturbance to neighboring cells.

Fast and energy-efficient update capability refers to how rapidly and efficiently large numbers of weight states can be adjusted during programming and erasing, and it therefore strongly influences the scalability of array-level operation (figure 4(c)). Because array-level learning requires repeated conductance modulation across many cells, low programming speed and repeated tuning can limit learning throughput while increasing time and energy overhead [76]. In addition, insufficient weight-update uniformity and reliability can increase the need for repeated program-verify operations, making this issue more critical as the array size increases.

A quantitative analysis of the additional energy and time overhead associated with program-verify operations in electrical programming showed that, in a resistive-memory crossbar, the write energy and latency were 3.391 nJ and 14.236 ns, respectively, without verification. When a single verification step was included, these values increased to 3.493 nJ and 19.389 ns, respectively. Thus, even one verification step increased the write energy by approximately 3.0% and the latency by approximately 36.2%. Because these overheads can accumulate when verification and corrective programming are repeated, reducing the number of program-verify operations is important for the implementation of large-scale arrays [77]. By contrast, optical programming does not require the programming stimulus to be delivered through shared row and column interconnects and can spatially confine the stimulus to selected cells or defined regions. Therefore, optical programming can update multiple cells in parallel while reducing the verification and correction operations associated with disturbances in unselected cells.

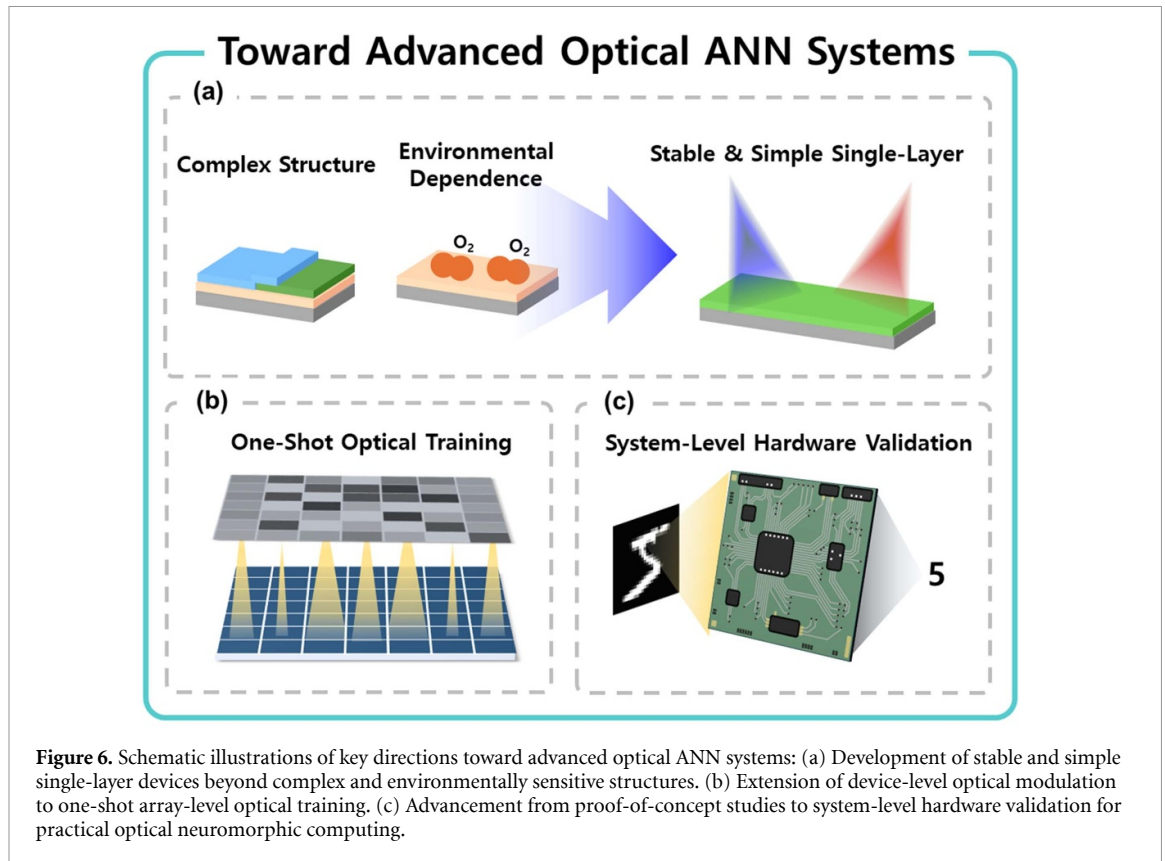
In addition, optoelectronic devices exhibit relatively low energy consumption during weight updates, further supporting their potential for large-scale array implementation. In a black phosphorus/CdS optoelectronic device, the estimated energy consumption was 0.43–8.9 fJ per optical spike, compared with 25 fJ per electrical spike in the same device. Under the reported conditions, the energy consumed per optical spike was therefore approximately 2.8–58 times lower than that consumed per electrical spike [78]. In another optoelectronic memristor based on an ITO/SiO<sub>2</sub>/Al<sub>2</sub>O<sub>3</sub>/Pt structure, the estimated energy consumption was 80 pJ per optical programming pulse, whereas the electrical programming energy was 18.36 nJ per pulse, corresponding to an approximately 230-fold reduction in programming-pulse energy [79]. These results quantitatively demonstrate the potential energy-saving advantages of optical conductance modulation at the individual-device level. When combined with spatially parallel weight updating, these energy advantages can further enhance the scalability of optical programming toward large-scale arrays.



### 3.2. Array-level applications in neuromorphic computing

Neuromorphic hardware minimizes data movement by directly utilizing stored device states for computation, thereby enabling parallel and energy-efficient information processing. These advantages become even more pronounced in array architectures, where the conductance state of each cell serves as a weight. As illustrated in figure 5, when input signals are simultaneously applied to each row, current responses determined by the stored conductance distribution are generated in parallel and accumulated along each column, so that each output reflects the weighted response of the input to the corresponding stored weight pattern [80, 81]. Thus, the significance of the array lies not merely in expanded storage capacity, but in its ability to directly generate computational responses from stored conductance patterns. This characteristic is particularly valuable for recognition tasks, such as Modified National Institute of Standards and Technology (MNIST) dataset, fingerprint, and face recognition, in which multiple spatial features should be compared simultaneously. After an input image is preprocessed into pixel and converted into corresponding input voltages, the resulting output current in each column depends on how strongly the input components overlap with high-conductance cells in the stored pattern. Columns with stronger overlap produce larger output currents, whereas those associated with lower-conductance regions yield smaller responses. By comparing the outputs from multiple columns, the array can determine which stored pattern best matches the input, providing the basis for both matching and classification [82, 83].

Although many previous studies have estimated classification accuracy by mapping experimentally measured multilevel conductance states of individual devices onto simulated array weights in software-based ANNs, such results primarily demonstrate the prospective utility of individual devices rather than the functionality of an integrated hardware ANN array [84]. Because learning and inference are not executed within a physical array, these evaluations cannot determine whether a target conductance distribution can be accurately established and preserved once many cells are integrated and operated collectively [85]. Even demonstrations extended to small-scale arrays, such as  $3 \times 3$  or  $5 \times 5$ , have largely been validated only at the level of simple visual memory, denoising, or pattern mapping, rather than establishing the feasibility of actual array-level computation. Such small-scale demonstrations do not sufficiently reveal the cumulative effects of cell-to-cell variation and disturbance in unselected cells during repeated updates, both of which increasingly govern computational fidelity as the array size grows. Consequently, establishing optically modulated devices as practical neuromorphic computing platforms requires more than simulation-based classification results or proof-of-concept small-array demonstrations; it requires direct evidence that large-scale arrays can implement and maintain the programmed conductance distribution needed for reliable MVM and practical image recognition.



#### 4. Conclusion and perspective

In this review, we have highlighted recent progress in optical conductance modulation for array-level ANN systems. From this perspective, optical learning offers two major advantages: it can confine weight-updating to selected cells without unintended conductance disturbance, and enable simultaneous and selective updating of multiple cells through controlled illumination. These characteristics make optical learning a promising strategy for improving weight-update reliability, training speed, and energy efficiency in hardware ANN systems. Nevertheless, several issues should still be resolved before this concept can be translated into practical hardware ANN platforms.

First, it is necessary to broaden the range of materials and device architectures capable of stable bidirectional optical conductance modulation as illustrated in figure 6(a). Most of the bidirectional optical conductance modulation devices reported to date are based on heterostructures composed of two active layers with different bandgaps [86, 87]. In these structures, not only the photoresponse of each material but also the interfacial band alignment, trap states, and barrier formation collectively influence device operation. Therefore, in large-scale integration processes, even slight variations in the interlayer junction state can lead to device-to-device variations in conductance modulation characteristics, making it difficult to achieve uniform and reproducible operation across the array. In addition, the strong dependence on specific material combinations and junction configurations further limits structural design flexibility. Although several single-material systems capable of bidirectional optical conductance modulation have also been reported, many of them rely on the adsorption and desorption of oxygen or moisture, or on changes in doping states induced by variations in the external environment. These mechanisms offer the advantage of enabling bidirectional modulation in a relatively simple manner under specific conditions, but they still suffer from limitations in terms of long-term stability against oxidation and operational stability under varying oxygen and moisture partial pressures. Therefore, to achieve stable bidirectional optical conductance modulation with high stability and simple device structures, it is important to develop single active layer systems that can provide reversible conductance modulation depending on the wavelength or optical stimulation conditions, without relying on complex interfacial engineering or external environmental factors, while maintaining structural and electrical stability under repeated optical operation.

Second, to fully realize the advantages of optical learning, device-level conductance modulation should be extended to array-level one-shot optical weight-update (figure 6(b)). Here, ultimate one-shot

optical learning refers to a scheme in which a single application of a spatially engineered optical stimulus directly sets each cell in the array to a different target conductance state, without sequential cell-by-cell scanning, repetitive pulse application, or subsequent correction steps. Most array-level optical learning studies reported to date have relied on binary transmission and blocking-pattern masks or multibeam-laser-based optical updating as strategies to enhance selectivity and parallelism and thereby improve learning efficiency [88, 89]. Although these strategies are effective for the selective learning of specific cells or local regions, they are not well suited for implementing complex weight distributions. In such cases, they require either multiple optical training steps with a series of masks or multiple light sources combined with sophisticated optical alignment systems. As a result, system complexity increases, and scalability toward large-area arrays is constrained. These limitations constitute a major barrier to the realization of one-shot optical weight modulation at the array level. To achieve this, a simple optical source should be able to deliver, in a single step, a spatially varying transmittance pattern or position-dependent light-intensity profile that encodes the target conductance of each cell, without relying on complex multi-source configurations or precise optical alignment systems. In conventional semiconductor microfabrication, grayscale-mask-based photolithography has been used to precisely control local exposure dose, and more recently, concepts such as active gray-tone masks or dynamic photomasks based on liquid-crystal devices have also been proposed [90, 91]. While these approaches have thus far been explored mainly in other fields, they can provide a useful conceptual and technical framework for optical weight-update schemes. Because such approaches can generate position-dependent optical stimulation intensities even with a single light source, they hold strong potential for extension into one-shot optical learning platforms that simultaneously assign target weights to individual cells. In other words, future research should move beyond simple cell selectivity toward directly encoding the weight matrix into the spatial distribution of light.

Finally, for optical learning to translate into practical neuromorphic computing hardware, it should advance beyond proof-of-concept demonstrations at the single-device or small-array level toward large-scale hardware implementation and extension to actual system level as shown in figure 6(c). Although many studies to date have demonstrated excellent optical conductance modulation characteristics at the single-device level, hardware-based computing with actual arrays has yet to be sufficiently realized and has instead largely been inferred indirectly from simulation results. However, in practical hardware ANNs, it is important to consider not only the performance of individual devices but also the robust realization of array-level characteristics, such as weight-update uniformity, reliability of conductance updates without unintended disturbance to unselected cells, and the efficiency of large-scale weight-updates. Therefore, whether these array-level characteristics can be stably maintained even in large-scale systems and translated into consistent weight-updating and reliable computing across the entire array should be validated through direct hardware-level demonstrations. Furthermore, for practical applications, the development of optical learning should proceed beyond proof-of-concept arrays toward integration at the system level [92]. Achieving this integration can be a critical step toward system-level neuromorphic hardware. Overall, optical weight modulation holds strong potential to overcome the structural limitations of conventional electrical learning schemes and to enable more precise and parallel array-level learning.

Compared with previously proposed reference benchmarks, current optically programmable devices have demonstrated meaningful progress in several key performance metrics. The proposed reference values for high-precision analog weight updates include a read voltage below 0.4 V, a weight-transfer or programming time below 1 ms, and more than 1000 effective programming steps under symmetric switching conditions [93]. Representative optically programmable devices have demonstrated a read voltage of 0.004 V and 4096 gradual conductance states, thereby reaching or exceeding the corresponding reference values for low-voltage readout and the number of conductance states [94, 95]. By contrast, the reported update time of 5 ms remains longer than the reference value of less than 1 ms [78]. Moreover, these achievements were obtained separately in different individual devices rather than being simultaneously realized within a single device or array. Nevertheless, these results indicate the potential for further advancement of optical programming technologies. For extension toward large-scale arrays, these device-level characteristics should be validated together with array-level programming uniformity, update reliability, operating speed, and energy efficiency.

Also, considering that neuromorphic systems ultimately aim to achieve on-chip learning, the energy advantages of optical learning should also be retained at the overall system level, including the energy consumption associated with light-source operation, optical transmission losses, and peripheral electronic circuits, rather than being limited to the optical energy incident on the device. In this context, an on-chip memory system combining optically controlled phase-change memory with silicon-photonics links was compared with an electrically controlled counterpart. Even when the electrical energy required

to drive the light source, optical transmission losses, and the energy consumption of major peripheral electronic circuits were included, the write and read energies per bit were approximately 5.97-fold and 3.8-fold lower, respectively [96]. Although this system is not itself a neuromorphic learning system, it demonstrates that the energy advantages of optical parallelism can be retained at the overall system level after the integration of the light source and peripheral electronics. These results support the potential extension of systems integrating optical weight modulation, on-chip optical delivery networks, and peripheral electronic circuits toward energy-efficient optical neuromorphic hardware.

Therefore, if the challenges discussed in the Conclusion and Perspective section are addressed, optical programming and erasing could evolve beyond a supplementary method of assisting electrical updates and emerge as a new paradigm for optically programmed ANNs systems. Furthermore, this progress is expected to accelerate the development of next-generation neuromorphic hardware with high reliability, high throughput, and scalability, ultimately laying an important foundation for the practical implementation of all-optically modulated neural networks.

## Acknowledgment

This research was supported by Seoul National University of Science and Technology.

## Data availability statement

No new data were created or analysed in this study.

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