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Retinocortical in-sensor neuromorphic vision platform for NIR-augmented artificial vision

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Abstract

In-sensor neuromorphic vision platforms with near-infrared (NIR) sensitivity are essential for intelligent imaging in low-light and multispectral environments. Here, a retinocortical dual-mode platform based on evolved-synaptic transistor (Evo-SynT) devices using upconversion nanoparticles (UCNP) and their integration into evolved-retina optical synapse (EROS) arrays is introduced. Evo-SynT devices exhibit key synaptic features, including paired-pulse facilitation indices exceeding 183.93% and 136.36% at a 0.5 s interval under 808 nm and 940 nm illumination, respectively, and analog weight modulation across 512 conductance states. A 12×12 EROS array enables dual-mode operation: retinal-like in-sensor preprocessing and cortical-like in-memory classification. The EROS array improves pedestrian detection accuracy under low-light conditions from 0.7806 to 0.8481 (808 nm) and 0.9071 (940 nm), and achieves classification accuracies of 77.19% and 79.40%, respectively. These results highlight the EROS platform as a scalable solution for integrated NIR-sensitive neuromorphic vision systems.

Introduction

The human visual system processes optical information through a hierarchical retinocortical pathway, where photoreceptors in the retina perform early-stage analog signal preprocessing, and the visual cortex conducts higher-order feature extraction and cognitive interpretation, as shown in Fig. 1a. Inspired by this biological model, artificial vision systems are increasingly adopting architectures that emulate both retinal and cortical functions in hardware, bridging early signal acquisition with downstream intelligence.¹⁻⁴ Such bioinspired retinocortical frameworks offer a promising foundation for developing next-generation vision computing platforms that operate beyond the visible spectrum. Indeed, while biological vision remains fundamentally constrained to visible wavelengths, artificial vision systems can exploit spectral regions such as near-infrared (NIR), which hold significant untapped potential for advanced perception.⁵⁻⁷

Extending artificial vision capabilities into the NIR range (~700-1000 nm) enables access to rich visual information beyond human perception. NIR light penetrates materials opaque to visible wavelengths, allowing imaging in low-light, dark, or visually obstructed conditions. This spectral advantage has driven the deployment of NIR-sensitive systems in fields such as autonomous driving, biomedical imaging, remote sensing, and security surveillance.⁸⁻¹¹ However, while sensing in this regime is well established, the challenge lies in processing large volumes of data in real time. Conventional architectures, which separate sensing and computation, often suffer from latency and bandwidth limitations. In response, in-sensor vision computing platforms are emerging as an effective solution, co-locating sensing and processing to enable immediate, energy-efficient interpretation of NIR visual data.¹²⁻¹⁶

Realizing such integrated NIR sensing and processing platforms at the device level critically depends on the intrinsic capabilities of the underlying semiconductor materials. Various emerging semiconductor candidates for NIR in-sensor vision computing, such as two-dimensional (2D) semiconductors and organic compounds, offer appealing advantages including strong light-matter interactions, mechanical flexibility, and tunable spectral responses.¹⁷⁻²⁰ However, despite these promising attributes, both 2D and organic semiconductors face critical drawbacks in achieving large-area integration, as well as stable and uniform operation—essential requirements for practical vision applications.²¹⁻²³ As a result, meeting the practical requirements of NIR in-sensor vision systems has remained a significant challenge.

In light of these limitations, metal-oxide semiconductors have drawn renewed interest as an alternative material platform for in-sensor vision computing devices. Metal-oxide semiconductors offer high electronic performance, excellent uniformity over large-area substrates, and good environmental stability, directly addressing the scalability and stability challenges of 2D and organic semiconductors.^{24-30,48,49} However, most metal-oxide semiconductors possess wide bandgaps. For instance, indium gallium zinc oxide (IGZO) exhibits a band gap of approximately 3.3 eV, which makes it effectively unresponsive to NIR light. This inherent limitation means that metal-oxide-based sensors cannot directly detect NIR signals, representing a critical drawback for NIR in-sensor vision computing applications.

In this research, we demonstrate a metal-oxide-based in-sensor vision computing platform, termed the evolved-retina optical synapse (EROS) array, which enables direct NIR signal detection and subsequent image processing within the array. The EROS array consists of a 12×12 pixel matrix, with each pixel comprising an IGZO-based evolved-synaptic transistor (Evo-SynT)—in which upconversion nanoparticles (UCNPs) convert incident NIR photons into ultraviolet (UV) or visible wavelengths detectable by the metal-oxide semiconductor, as shown in **Fig. 1b**. This design endows each pixel with direct NIR sensitivity at 808 nm and 940 nm, enabling reliable image acquisition under low-light conditions beyond the visible spectrum. Furthermore, by leveraging the uniform, large-area deposition of metal-oxide-based electronics, the EROS array achieves consistent performance across all pixels, overcoming the scalability and uniformity limitations of prior 2D- or organic-based devices. As shown in **Fig. 1c** and **Supplementary Fig. 1**, this platform operates in dual modes—retina-like preprocessing for enhancing NIR imagery in low-visibility conditions, and cortex-like neuromorphic postprocessing for generating analog synaptic outputs suitable for subsequent neural network-based classification. These findings demonstrate a near-infrared sensitive in-sensor vision computing platform that integrates early-stage signal acquisition with downstream information processing, offering a viable route toward machine vision systems that operate beyond the spectral range of human perception.

Result and Discussion

Upconversion enabled near infrared synaptic behavior

To enable NIR photoresponsivity in the Evo-SynT, UCNPs were employed as internal spectral converters. UCNPs are luminescent nanomaterials that convert NIR light into higher-energy UV or visible emissions through a multiphoton process known as photon upconversion.³¹ Typically built from a NaYF₄ host lattice doped with Yb³⁺ sensitizers and activator ions such as Tm³⁺ or Er³⁺, UCNPs exhibit sharp emission peaks, long lifetimes, and high photostability.^{32,33} Among various UCNP candidates, NaYF₄ co-doped with Yb and Tm (NaYF₄:Yb/Tm) nanoparticles were introduced due to their ability to emit UV and blue photons, which spectrally overlap with the optical absorption range of IGZO, enabling efficient photocarrier generation under upconverted illumination.³⁴ NaYF₄:Yb/Tm nanoparticles were synthesized via thermal decomposition in oleic acid and 1-octadecene, a well-established route for producing monodisperse nanocrystals with high upconversion efficiency. Transmission electron microscopy (TEM) and dynamic light scattering (DLS) confirmed a uniform spherical morphology with an average diameter of 34 ± 1.3 nm (**Fig. 2a** and **Supplementary Fig. 2**). Elemental mapping using energy-dispersive X-ray spectroscopy (EDS) revealed homogeneous spatial distribution of Y, F, Yb, and Tm ions across the surface (**Fig. 2d**), with quantitative analysis indicating doping levels of 6.21% Yb and 0.99% Tm consistent with commonly used doping levels for efficient upconversion and minimal concentration quenching.³⁵

To evaluate the upconversion property of UCNPs, photoluminescence (PL) spectrum of the synthesized NaYF₄:Yb/Tm nanoparticles were measured under 980 nm NIR laser excitation at a power intensity of 500 mW cm^{-2} , as shown in **Fig. 2b**. Under 980 nm excitation, the UCNPs exhibited sharp photoluminescence peaks at 344 nm ($^1\text{I}_6 \rightarrow ^3\text{F}_4$), 360 nm ($^1\text{D}_2 \rightarrow ^3\text{H}_6$), 450 nm ($^1\text{D}_2 \rightarrow ^3\text{F}_4$), and 473 nm ($^1\text{G}_4 \rightarrow ^3\text{H}_6$), which are characteristic of Tm³⁺ transitions.³⁴ These emissions result from sequential energy transfer between Yb³⁺ sensitizers and Tm³⁺ activators. In this system, Yb³⁺ acts as a sensitizer: upon absorbing 980 nm photons, Yb³⁺ ions are excited from the $^2\text{F}_{7/2}$ to the $^2\text{F}_{5/2}$ level and subsequently transfer their energy to neighboring Tm³⁺ ions (**Fig. 2c**).³⁶ These results confirm the upconversion functionality of the NaYF₄:Yb/Tm nanoparticles, whereby absorbed NIR photons are converted into higher-energy emissions through multiphoton excitation processes.

Based on the verified optical functionality and structural uniformity of the NaYF₄:Yb/Tm nanoparticles, the Evo-SynT device was fabricated by embedding the UCNPs between two IGZO active layers, as shown in **Fig. 2e**. The detailed fabrication process is described in **Supplementary Fig. 3** and the methods section. This embedded structure maximizes photonic interaction within the active region while minimizing interfacial degradation, enhances photon-to-carrier conversion efficiency, and ensures long-term stability under optical stimulation by confining the upconverted emissions near the IGZO interface. UV–Vis–NIR absorption measurements further confirmed this optical enhancement, with the IGZO/UCNP/IGZO sandwich structure exhibiting substantially higher absorbance in the 808 and 940 nm regions compared to pristine IGZO film or IGZO/UCNP bilayers (**Supplementary Fig. 4**), validating the effectiveness of the vertical stacking strategy for NIR light harvesting.

To evaluate the device-level photoresponse of the upconversion-assisted Evo-SynT, transfer characteristics were measured under NIR irradiation at 808 nm and 940 nm with V_{DS} of 10.1 V. As shown in **Fig. 2f** and **2g**, the device exhibited increasing drain current and negative shift with rising optical power at both wavelengths, confirming NIR responsiveness. These observations verify that the integrated UCNPs play a central role in enabling deep NIR sensitivity in the Evo-SynT. To confirm that the upconverted light emitted by the UCNPs can be effectively absorbed by the IGZO channel, the optical absorption characteristics of IGZO were analyzed. As shown in **Supplementary Fig. 5**, the Tauc plot extracted from ultraviolet–visible (UV–vis) spectroscopy reveals an optical bandgap of approximately 3.21 eV, which corresponds to the absorption of photons in the ultraviolet and blue spectral regions. This result confirms that the upconverted emissions from the UCNPs fall within the absorbable energy range of the IGZO channel.

To quantify this energy transfer efficiency, we performed a spectral overlap–based analysis. We defined the optical coupling efficiency (η_{coupling}) as the ratio of the absorbed photon flux to the total emitted flux, calculated by integrating the overlap between the UCNP emission spectrum and the IGZO spectral absorptance:

$$\eta_{\text{coupling}} = \frac{\int \Phi_{\text{UCNP}}(\lambda) A_{\text{IGZO}}(\lambda) d\lambda}{\int \Phi_{\text{UCNP}}(\lambda) d\lambda} \times 100 (\%) \quad (1)$$

where $\Phi_{\text{UCNP}}(\lambda)$ represents the UCNP photon flux spectrum and $A_{\text{IGZO}}(\lambda)$ is the wavelength dependent absorption probability of the IGZO channel.

This calculation yields an estimated η_{coupling} of approximately 21.6%, confirming that the dominant NaYF₄:Yb/Tm emission peaks (e.g., 290 nm, 345 nm, 360 nm) are effectively harvested by the active layer. Crucially, while typical NaYF₄:Yb/Tm systems exhibit a modest internal upconversion quantum yield (UCQY) of 0.5–4%, the high optical coupling combined with the intrinsic photoconductive gain of the transistor compensates for the limited photon flux.^{32,33,52,53}

The UV and blue photons generated by UCNPs possess sufficient energy to excite trap states associated with deep-level neutral oxygen vacancies (V_{O}) within the IGZO channel. Upon photoexcitation, deep-level neutral V_{O} centers are ionized into donor-like states such as V_{O}^+ and V_{O}^{2+} near the conduction band, releasing electrons into the channel (e.g., $V_{\text{O}}^0 \rightarrow V_{\text{O}}^+ + e^-$ or $V_{\text{O}}^0 \rightarrow V_{\text{O}}^{2+} + 2e^-$), as shown in **Supplementary Fig. 6**. This process significantly increases channel conductivity under illumination. Furthermore, the ionized V_{O} states are metastable, and their recombination is kinetically hindered, leading to a prolonged photocurrent decay even after the removal of light.^{37,38,50} This persistent photoconductance (PPC) behavior enables the device to retain optical memory, supporting its operation as a photo-synaptic element in neuromorphic vision systems. This PPC mechanism, involving V_{O} ionization and slow recombination kinetics, is consistent with prior observations in IGZO, further validating the oxygen vacancy origin of PPC in Evo-SynT.⁵¹

To confirm that the NIR photoresponse originates specifically from the UCNP-mediated upconversion process, control devices without UCNPs or with only the dispersing solvent were tested, as shown in **Supplementary Fig. 7**. Both configurations showed negligible response under 808 nm and 940 nm illumination, validating that the observed photocurrent in Evo-SynT is exclusively attributed to the upconverted emissions from NaYF₄:Yb/Tm nanoparticles. To further ensure that the observed photocurrent does not originate from thermal effects but exclusively from the upconversion process, we additionally conducted in-situ temperature measurements under prolonged 808 nm illumination at a power density of 1 W/mm² for 10,000 s. The p⁺-Si/SiO₂/IGZO was tested. The sample exhibited a temperature increase from 24.35 °C to 47.77 °C, as shown in **Supplementary Fig. 8**. Considering that typical measurement durations are on the order of 10 s, during which the temperature remained close to room temperature, these results confirm that the

photoresponse is not thermally driven but is a direct consequence of UCNP-mediated upconversion.

To investigate the synaptic behavior of the upconversion-assisted Evo-SynT, its ability to retain photocurrent after pulsed optical stimulation was first examined. Postsynaptic current (PSC) measurements were performed under pulsed NIR illumination at 808 nm and 940 nm with $V_{DS} = 0.5$ V. As shown in **Fig. 2h** and **2j**, 808 nm and 940 nm light pulses were applied for 5 s, under varying power densities, and the drain current was monitored for 60 s following light-off. In both wavelength regimes, the device exhibited a power-dependent increase in peak PSC followed by a gradual decay, indicative of synaptic relaxation behavior. The inset graph in **Fig. 2h** and **2j** shows the extracted PSC values measured 60 s after light-off for each power condition. To more clearly visualize the retention behavior, the PSC values at 70 s were plotted as a function of optical intensity in **Fig. 2i** and **2k**. Starting from an initial dark current of approximately 0.05 nA, the PSC increased from 0.21 nA to 2.15 nA under 808 nm, and from 0.18 nA to 0.71 nA under 940 nm, as the power intensity increased from 13 mW mm⁻² to 1325 mW mm⁻². These results demonstrate that the Evo-SynT can function as a photo-synaptic element capable of encoding input strength into persistent electrical states, validating its potential for vision-inspired neuromorphic computing.

Demonstration of upconversion enabled synaptic functionality

To comprehensively evaluate the synaptic functionality of the upconversion-assisted Evo-SynT, a series of electrical measurements were performed under NIR optical stimulation. These include paired-pulse facilitation (PPF) to probe short-term plasticity (STP), transition from STP to long-term potentiation (LTP) under repeated stimuli, as well as reversible potentiation/depression cycles and conductance linearity—collectively demonstrating the device's capacity to emulate essential forms of learning and memory at the hardware level.^{39,40}

As an initial indicator of STP, PPF measurements were conducted under pulsed NIR illumination at 808 nm and 940 nm, as shown in **Fig. 3a**. PPF, a characteristic STP response, reflects enhanced PSC upon a second stimulus due to residual carrier effects. The PPF index is quantitatively defined as:

$$PPF\ index\ (\%) = \left(\frac{A_2}{A_1} \right) \times 100 \quad (2)$$

where A_1 and A_2 represent the amplitudes of the first and second postsynaptic current peaks, respectively. The device exhibited a maximum PPF index of 183.93% at 0.5 s under 808 nm, and 136.36% at the same interval under 940 nm. In both cases, the PPF index decayed exponentially with increasing inter-pulse interval (ΔT), consistent with biologically inspired facilitation dynamics. These findings confirm that the Evo-SynT reliably reproduces STP behavior under optical stimulation.

To explore the transition from STP to LTP, a fundamental mechanism underlying learning and memory, key stimulation parameters were systematically modulated under 808 nm and 940 nm excitation. First, the PSC was measured at increasing pulse frequencies while maintaining a constant light power density of 13 mW mm^{-2} , revealing frequency dependent synaptic potentiation as shown in **Fig. 3b** and **3c**. Under 808 nm, the PSC increased from 0.19 nA at 0.2 Hz to 0.61 nA at 1 Hz, while 940 nm excitation resulted in a rise from 0.06 nA to 0.23 nA. Next, varying the optical power density also enhanced PSC magnitude, reaching 4.24 nA for 808 nm and 0.69 nA for 940 nm at the highest intensity of 266 mW mm^{-2} , as shown in **Fig. 3d** and **3e**. Additionally, as shown in **Supplementary Fig. 9a** and **9b**, increasing the number of pulses at fixed frequency and intensity led to a gradual shift from transient to sustained PSC, demonstrating long-term conductance retention. Quantitative analysis of the gain (A_n/A_1) showed increasing values with both frequency and intensity, reaching maximum values of 4.48 for 808 nm and 2.82 for 940 nm at a higher frequency of 1 Hz, and values of 14.98 for 808 nm and 9.46 for 940 nm at 266 mW mm^{-2} , as shown in **Fig. 3f** and **3g**. These results confirm that Evo-SynT exhibits dynamic modulation of synaptic strength in response to optical stimulation, effectively emulating the transition from STP to LTP observed in biological synapses.

To further evaluate the synaptic functionality of the upconversion-assisted Evo-SynT, repetitive potentiation and depression experiments were carried out under both 808 nm and 940 nm excitation, focusing on the linearity, stability, and bidirectional tunability of conductance modulation. Under 808 nm illumination (13 mW mm^{-2} , 1 Hz), the Evo-SynT exhibited a highly linear increase in conductance across 512 consecutive pulses (**Fig. 3h** and **Supplementary Fig. 10a**), demonstrating reliable potentiation with discrete state evolution. This was achieved without any gradual increase in light intensity, which is favorable for low power operation. A similarly robust potentiation trend was observed under 940 nm excitation (**Fig. 3j** and **Supplementary Fig. 10b**), confirming consistent behavior across wavelengths.

Depression behavior was investigated by applying a gate bias of 1.5 V for 808 nm and 1.0 V for 940 nm following the optical pulses. To justify these electrical depression conditions, we additionally performed single-pulse transient and relaxation measurements with systematically varied pulse amplitudes and durations, which are provided in the **Supplementary Fig. 11**. These measurements establish that a pulse duration of 0.5 s with gate biases of 1.5 V (for 808 nm) and 1.0 V (for 940 nm) yields reliable and controlled synaptic depression without inducing excessive over-erasure or instability. For the synaptic weight curves shown in **Fig. 3i** and **3k**, both optical potentiation and electrical depression were implemented using pulse trains at 1 Hz. Optical pulses (808 or 940 nm, 13 mW mm⁻²) were applied to program LTP, and electrical gate pulses were used to induce long-term depression (LTD). In all cases, the PSC was read out 0.5 s after each pulse to suppress fast transient and capacitive components and to ensure that the extracted values represent quasi-steady synaptic weights, following the protocol commonly used in photonic synapse studies.

As illustrated in **Fig. 3i** and **3k**, the Evo-SynT exhibited symmetric conductance modulation, with PSC values returning to baseline levels in a controlled and reversible manner. To quantitatively assess the linearity of synaptic weight modulation, a nonlinearity (NL) metric was introduced based on exponential fitting of the potentiation and depression characteristics. The weight update behavior under optical stimulation was modeled using the following exponential equations:

$$G_P(t) = B \left(1 - e^{\left(\frac{-t}{A_P}\right)} \right) + G_{MIN} \quad (3)$$

$$G_D(t) = (G_{MAX} - C)e^{\left(\frac{-t}{A_D}\right)} + C \quad (4)$$

where $G_P(t)$ and $G_D(t)$ are the conductance during potentiation and depression at time t , respectively, t is the number of optical stimulation pulses, G_{MAX} and G_{MIN} are the maximum and minimum conductance values, respectively, A_P and A_D are the characteristic nonlinearity parameters for potentiation and depression, respectively, and B and C are fitting constants related to the scaling of conductance range and initial offset. The NL was then calculated as:

$$NL = \frac{t_{MAX}}{A} \quad (5)$$

where t_{MAX} is the total number of pulses. Smaller NL values correspond to slower and more linear updates.^{41,42} Under 808 nm illumination, A_P was 360.59 and depression nonlinearity A_D was 4290.07, resulting in NL values of 1.42 for potentiation and 0.093 for depression. For 940 nm, A_P was 6.63×10^6 and A_D was 13660.39, with NL values of 7.72×10^{-5} for potentiation and 0.029 for depression. These findings confirm that the Evo-SynT enables highly linear and symmetric potentiation and depression behaviors across numerous conductance states, making it well suited for precise and scalable synaptic weight modulation in neuromorphic computing platforms.

To further verify that these multilevel synaptic states are not transient artifacts but represent physically stable states, retention measurements were conducted for both optically potentiated and electrically depressed levels, as shown in **Supplementary Fig. 12 and 13**.⁵⁴ Distinct synaptic states were first programmed using defined numbers of optical or electrical pulses, and the postsynaptic current was read 10 s after the final pulse to suppress fast transient components. The PSC was then monitored for 100 s and analyzed by linear fitting to evaluate state stability. Using a state-separability criterion based on inter-level spacing, the optically programmed LTP states remained distinguishable for 57 s (64 pulses) up to 795 s (1 pulse) at 808 nm and 68 s (64 pulses) up to 803 s (1 pulse) at 940 nm. For electrical depression, the LTD states remained separable for 70 s (64 pulses) up to 600 s (1 pulse) at 1.5 V and 120 s (64 pulses) up to 900 s (1 pulse) at 1.0 V, confirming stable multilevel electrical erasure with voltage-dependent retention strength.

To evaluate the endurance of the programmed synaptic states under realistic learning conditions, prolonged optical–electrical cycling tests were performed. The Evo-SynT was repeatedly trained using alternating optical potentiation and electrical depression for a total of 1500 cycles, mimicking extended learning and forgetting processes, as shown in **Supplementary Fig. 14**. Throughout this endurance test, the devices maintained stable and controllable postsynaptic current modulation without abrupt degradation or loss of switching functionality, demonstrating that the UCNP-integrated heterostructure can withstand repeated photo-electrical stress. This result confirms that the multilevel synaptic states are not only retained over time but also preserved under long-term repeated operation, supporting the reliability of the Evo-SynT platform for neuromorphic optoelectronic systems.

These results collectively demonstrate that the Evo-SynT reliably emulates key synaptic behaviors—including STP and LTP, linear and reversible weight modulation, and frequency-dependent learning—under biologically inspired stimulation protocols. Unlike conventional

phototransistors, which typically exhibit monotonic and intensity-dependent responses, Evo-SynT shows sensitivity to the temporal dynamics of optical pulses such as frequency, interval, and pulse count. This temporal dependence reflects neuromorphic functionality and distinguishes the Evo-SynT from simple phototransduction-based devices. A performance comparison with recently reported NIR synaptic devices (**Supplementary Table 1**) confirms that Evo-SynT outperforms existing technologies in terms of responsivity, energy efficiency, and recognition accuracy.

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Array integration for in sensor neuromorphic vision

To validate the system-level applicability of the upconversion-assisted Evo-SynT, a 12×12 -pixel EROS array was constructed on a glass substrate, where each pixel integrates an Evo-SynT and an IGZO-based switching transistor in a two-transistor (2T) configuration, as shown in **Fig. 4a** and **Supplementary Fig. 15a**. This architecture enables spatially distributed NIR sensing and synaptic processing across the matrix, supporting precise pixel-level readout and electrical isolation. The vertically stacked IGZO/UCNP/IGZO trilayer structure within each Evo-SynT enhances light absorption while minimizing lateral footprint, yielding a high optical aperture ratio of 70.2% and a geometric fill factor of 35.7%. These features collectively demonstrate a scalable, uniform, and energy-efficient hardware platform for in-sensor neuromorphic vision systems.⁴³

To validate the device fabrication and functionality of the EROS array, photographic and microscope images in **Fig. 4b–d** and **Supplementary Fig. 15b** confirm the successful patterning and integration of the optical synaptic pixels, including clearly defined sensing and switching lines across the 12×12 matrix. The multilayered device architecture is further detailed in **Supplementary Fig. 16**, with complete fabrication procedures described in the Methods section. Pixel-wise electrical characterization was performed by applying a 1 V bias to the data line, sweeping the scan line voltage from -10 V to 10 V, and activating the switching transistors using a 5 V gate bias. As shown in **Supplementary Fig. 17**, the resulting sensing line current (I_{SL}) exhibited uniform and stable characteristics across all pixels, confirming high device yield and reliable operation throughout the array.

To demonstrate neuromorphic functionality at the array level, a cyclic learning-relearning process (learn–forget–1st relearn–forget–2nd relearn) was applied to the EROS array under alternating NIR stimulation. As schematically illustrated in **Fig. 4e**, optical patterns corresponding to the letters “Y” and “S” were projected onto the array using 808 nm and 940 nm illumination, respectively. Following initial memory encoding, memory decay was induced via dark relaxation, and subsequent reactivation was achieved through relearning cycles. The array was measured using a passive matrix configuration, where conductance changes in individual pixels were read out via line-by-line electrical addressing under scan line voltage 1 V. During each learning and relearning phases, the optical stimulation was applied at a pulse frequency of 1 Hz with a power density of 13 mW mm^{-2} . The 3D surface plot in **Fig. 4f** displays the I_{SL} distribution across 42 pixels for the “Y” pattern under 808 nm excitation, corresponding to the spatial activation shown in

Supplementary Fig. 18a. As shown in **Supplementary Fig. 18b**, all pixels exceeded the 0.3 nA threshold during initial learning (20 pulses), with reactivation requiring only 5-6 and 3-4 pulses in the first and second relearning cycles, respectively. **Supplementary Fig. 19a** shows median I_{SL} evolution through dark relaxation (0.01 pA $\rightarrow$ 0.05 nA $\rightarrow$ 0.12 nA), while **Supplementary Fig. 19b** confirms reduced relearning pulse counts (16 $\rightarrow$ 2-3 $\rightarrow$ 1-2), collectively indicating stable and cumulative synaptic encoding. A comparable behavior was observed for the “S” pattern under 940 nm excitation, as shown in **Fig. 4g** and **Supplementary Fig. 20a**. **Supplementary Fig. 20b** demonstrates that all 46 addressed pixels exceeded the 0.15 nA threshold, and statistical summaries in **Supplementary Fig. 21a** and **21b** further reveal a progressive increase in median ISL (0.002 nA $\rightarrow$ 0.040 nA $\rightarrow$ 0.048 nA) and reduction in pulse counts (17 $\rightarrow$ 3-4 $\rightarrow$ 1-2) over successive learning cycles. These results validate the EROS array’s ability to encode, retain, and rapidly recover spatially distributed memory through repeated optical stimulation, underscoring its capability for robust in-sensor learning.

While the current array demonstrates proof-of-concept functionality, its scalability toward high-resolution neuromorphic systems is further addressed in **Supplementary Discussion 1**, including design strategies to mitigate optical and electrical crosstalk, ensure addressability, and support flexible frame-rate operation. In addition, as shown in **Supplementary Fig. 22**, the operational reliability of the array under repeated optical–electrical synaptic cycling is quantitatively evaluated, demonstrating stable and reproducible conductance modulation over multiple write–erase sequences, which is essential for large-scale neuromorphic deployment.

Retinocortical near infrared neuromorphic vision computing

To demonstrate the practical utility of the EROS array for real-world vision computing applications, two simulation scenarios were explored: an in-sensor preprocessing task for NIR-based image enhancement under low-light conditions, and an in-memory post-processing task employing transformer-based classification.

As a first step, the in-sensor preprocessing task was implemented to enhance pedestrian detection under low-light conditions by leveraging the EROS array's NIR sensitivity. As shown in **Fig. 5a**, the Low Light Visibility Infrared Pedestrian (LLVIP) dataset, containing challenging nighttime visible-light images, was selected to highlight the EROS array's ability to extend visual detection beyond human perception.⁴⁴ Utilizing experimentally measured optoelectronic characteristics, the device response $I(x)$ under incident NIR intensity x (mW mm^{-2}) was modeled by a second-order polynomial:

$$I(x) = ax^2 + bx + c \quad (6)$$

with fitted coefficients $a = 4.61 \times 10^{-16}$, $b = 1.03 \times 10^{-12}$, and $c = 6.51 \times 10^{-11}$ (808 nm) and $a = 7.52 \times 10^{-17}$, $b = 3.81 \times 10^{-13}$, and $c = 3.45 \times 10^{-11}$ (940 nm). Here, all x values directly extracted from the experimental NIR power conditions applied to the physical Evo-SynT devices in EROS array. This approach ensures that the simulated image response is quantitatively grounded in real hardware behavior. For visual representation, raw data were normalized into 8-bit grayscale images via a logarithmic mapping⁴⁵:

$$G(x) = \frac{\log(1 + I(x)) - \log(1 + I_{min})}{\log(1 + I_{max}) - \log(1 + I_{min})} \times 255 \quad (7)$$

This preprocessing strategy, mimicking the neuromorphic visual processing of the EROS array, significantly enhanced pedestrian visibility under low illumination, as depicted in **Fig. 5b-d** and **Supplementary Fig. 23**. To quantify effectiveness, pedestrian detection was evaluated using the YOLOv8n model after 50 epochs of training. As shown in **Fig. 5e-h**, compared with baseline visible images (precision: 0.7806, recall: 0.6407, mean average precision at intersection over union (IoU) threshold 0.5 (mAP@0.5): 0.7190), the NIR-enhanced images under 808 nm illumination yielded marked improvements (precision: 0.8730, recall: 0.7502, mAP@0.5: 0.8481). Further

enhancements at 940 nm provided optimal results (precision: 0.9071, recall: 0.8047, mAP@0.5: 0.8869). These findings validate the practical capability of the EROS array to perform intelligent, sensor-level image enhancement, emphasizing its potential as a preprocessing front-end in low-light vision computing systems.

Following the demonstration of EROS array capabilities in preprocessing, its application was further extended to transformer-based image classification using an in-memory computing framework. Employing the Tiny ImageNet dataset for benchmarking, a Vision Transformer (ViT) model was selected due to its complexity and suitability for evaluation (**Fig. 6a**).⁴⁶ The experimentally measured potentiation and depression characteristics of the EROS array were mapped onto the transformer's multi-layer perceptron (MLP) synaptic weights, enabling analog weight encoding and low-power inference (**Fig. 6b**, **Supplementary Fig. 24a** and **24b**).

Synaptic programming errors were experimentally characterized for 10 devices under 808 nm and 940 nm illumination as shown in **Supplementary Fig. 25a** and **25b**.⁴⁷ Linear fitting yielded state-proportional error coefficients (α) of 0.0589 for 808 nm and 0.0767 for 940 nm, with both datasets achieving linearity (R^2) greater than 0.9 and remaining within the acceptable error range ($\alpha < 8\%$). The extracted α -values served as direct inputs for the CrossSim inference simulations presented, thereby ensuring that the modeled synaptic variations reproduce experimentally observed programming errors. These results correspond to stable classification accuracy of 77.19% (808 nm) and 79.40% (940 nm), as shown in **Fig. 6c–e**. Confusion matrices under both wavelengths showed distinct diagonal dominance, indicating robust class discriminability as shown in **Fig. 6f** and **6g**. To provide further granularity, **Supplementary Fig. 26** presents class-wise accuracy distributions under both NIR conditions. Notably, the 808 nm case maintains higher accuracy across several classes (e.g., 98%, 96%, 94%), whereas the 940 nm case exhibits slightly more variation with a few lower-performing categories (e.g., 62%, 64%), yet still preserves reliable detectability overall.

The classification results were further analyzed using t-distributed stochastic neighbor embedding (t-SNE), revealing clearly separated semantic clusters under both illumination conditions as shown in **Fig. 6h** and **6i**. These findings confirm that the EROS array maintains sufficient resolution and linearity of analog weights, effectively supporting transformer-based neuromorphic classification tasks. Overall, the EROS platform successfully demonstrates

retinocortical functionality, serving both preprocessing and post-processing roles in integrated neuromorphic vision systems.

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This study presents a retinocortical neuromorphic vision architecture that integrates broadband photodetection, synaptic encoding, and dual-mode processing capabilities within a unified device array. By introducing the Evo-SynT, the platform extends spectral perception into the near-infrared regime while simultaneously enabling analog memory formation and temporal signal modulation. The EROS array, constructed from Evo-SynT units, operates in both in-sensor preprocessing and post-processing classification modes, thereby replicating key functional elements of the biological visual pathway. Experimental results demonstrate reliable spectral enhancement, robust neuromorphic behavior, and substantial improvements in AI model performance under low-visibility conditions. This work not only advances the functional integration of sensing and computing in optoelectronic systems but also lays the groundwork for future development of intelligent vision hardware capable of dynamic, context-aware optical cognition across broad spectral domains.

Methods

Synthesis of NIR responsive NaYF₄:Yb/Tm core UCNP

Rare-earth lanthanide precursor solutions were prepared prior to chemical synthesis. YCl₃ and YbCl₃ were each dissolved in deionized water at a concentration of 1 M, while TmCl₃ was prepared at 0.03 M. The solutions were vortexed and sonicated until fully clarified. For the NaOH/NH₄F mixture, 0.10 g of NaOH was sonicated in 5 mL of methanol, followed by the addition of 0.148 g of NH₄F under vigorous stirring. This solution was freshly prepared for each synthesis.

Under an argon atmosphere, 0.747 mL of YCl₃, 0.25 mL of YbCl₃, and 0.1 mL of TmCl₃ were combined in a 100-mL three-necked round-bottom flask and heated to 110 °C for 15 minutes to evaporate residual water. A magnetic stir bar was used to maintain constant agitation at 300–400 rpm throughout the synthesis. Subsequently, 6 mL of oleic acid and 15 mL of 1-octadecene were added, and the mixture was heated to 150 °C until the solution became a clear pale yellow.

After cooling to 60 °C, 5 mL of the methanol-based NaOH/NH₄F mixture was introduced. The solution was then heated to 110 °C for 20 minutes to remove methanol, followed by a 10-minute vacuum step to eliminate any residual solvent. Complete removal of methanol and water at this stage is essential to prevent undesirable side reactions. Three consecutive cycles of vacuum and argon purging were conducted, each lasting one minute.

The temperature was increased to 300 °C and maintained for 1 hour under continuous stirring to complete the nanoparticle formation. Upon completion, the reaction mixture was cooled to room temperature and transferred to a 50 mL conical tube. The round-bottom flask was rinsed three times with acetone to recover any remaining particles. The total volume in the conical tube was adjusted to 40 mL with acetone and centrifuged at 6,654 g for 10 minutes. The resulting pellet was redispersed in 20 mL of hexane using vortex mixing. A final centrifugation at 1,000 g for 10 minutes was performed, and the clear hexane supernatant containing the nanoparticles was collected into a glass vial.

Fabrication of Evo-SynT

The Evo-SynT devices were fabricated using a three-terminal bottom-gate configuration. A heavily doped p⁺-Si wafer with a thermally grown 120-nm-thick SiO₂ layer served as both the substrate and the gate dielectric, with the underlying silicon functioning as the gate electrode. A 20 nm a-IGZO film was deposited on top of the SiO₂ layer by radio frequency (RF) magnetron

sputtering at room temperature under a working pressure of 5 mTorr in argon ambient. The IGZO sputtering target consisted of $\text{In}_2\text{O}_3\text{:Ga}_2\text{O}_3\text{:ZnO}$ in a 1:1:1 molar ratio.

Following the initial IGZO deposition, a layer of UCNPs ($\text{NaYF}_4\text{:Yb/Tm}$ core) was spin-coated onto the IGZO surface at 1000 rpm for 30 s. Subsequently, an additional 20 nm IGZO layer was deposited under identical sputtering conditions, encapsulating the UCNP layer. The stacked IGZO and UCNP layers underwent post-deposition annealing at 300 °C for 1 h and 100 °C for 30 min, respectively.

Finally, aluminium (Al) source and drain electrodes were defined via e-beam evaporation using a precision-aligned shadow mask to form well-defined channels. The resulting devices featured a channel width of 1000 μm and length of 150 μm .

Fabrication of EROS array

To demonstrate the EROS array, thin-film transistor arrays were fabricated on a glass substrate. A chromium (Cr)/gold (Au) (5/45 nm) gate electrode was deposited by thermal evaporation and patterned through a standard photolithography process. Subsequently, as gate insulator, a 55 nm-thick aluminium oxide (Al_2O_3) layer was deposited by atomic layer deposition process at 150 °C. The channel layer comprises upconversion nanoparticles embedded between two 20 nm-thick IGZO films. Both the top and bottom IGZO layers were deposited by RF magnetron sputtering using an IGZO sputtering target, patterned by photolithography and thermally annealed at 300 °C for 60 min. The UCNPs were spin-coated, patterned by lift off process and thermally annealed 100 °C for 30 min. The Al_2O_3 layer was patterned using photolithography to form contact holes. Lastly, as source and drain electrodes, a 75 nm-thick Al layer was deposited by thermal evaporation and patterned through a lift-off process. The fabricated TFTs had a channel width and length of 100 μm and 50 μm for Evo-SynT and 100 μm and 10 μm for switching TFT, respectively.

Characterization of UCNP

The characteristics of $\text{NaYF}_4\text{:Yb/Tm}$ core upconversion nanoparticles (UCNPs) were analyzed using transmission electron microscopy (JEM-F200, JEOL) and field emission scanning electron microscopy (JSM-7610F-Plus, JEOL), along with energy-dispersive X-ray spectroscopy mapping for elemental distribution. Hydrodynamic size was determined via dynamic light scattering using

a SZ-100 system (Horiba). Upconversion luminescence spectra were obtained using a Fluorolog-QM photoluminescence spectrometer (Horiba) under excitation by a 980 nm laser.

Device characterization and simulation

The electrical properties of the Evo-SynT devices and EROS array were characterized at room temperature under dark conditions using a parameter analyzer (Model 4200A, Keithley Instruments). To investigate the NIR photoresponse, laser sources (Cubecell Technology) with wavelengths of 808 nm and 940 nm were employed. The incident power densities were systematically varied across seven levels: 13, 127, 255, 510, 764, 1019, and 1325 mW mm⁻². To generate pulsed light stimuli, the lasers were modulated through a function/arbitrary waveform generator (UTG1010A, UNI-T), enabling controlled temporal stimulation of the synaptic devices.

To verify the presence and distribution of the NaYF₄:Yb/Tm core UCNPs, field emission-scanning electron microscopy (FE-SEM) (JSM-7610F-Plus, JEOL) and energy-dispersive X-ray spectroscopy (EDS) mapping were performed. The upconversion luminescence behavior of the UCNPs was characterized using a photoluminescence spectrometer (FS5, Edinburgh Instruments) under 980 nm laser excitation at a power intensity of 500 mW cm⁻². The optical bandgap of the IGZO layer was determined using ultraviolet–visible (UV–vis) spectroscopy (V-650, JASCO).

For neuromorphic performance evaluation, a two-stage artificial vision simulation was conducted. In the image pre-processing module, the Low-Light Visibility Infrared Pedestrian (LLVIP) dataset was used in conjunction with the You Only Look Once version 8 nano (YOLOv8n) architecture to enhance visibility under low-light NIR conditions. In the subsequent image classification stage, the Tiny ImageNet dataset was processed using a Vision Transformer (ViT) model within the CrossSim framework to assess the system's classification accuracy and robustness under varying irradiation conditions.

Schematic illustrations

Schematic illustrations and 3D renderings were created while creating Figure 1a-c, 2c, 2e, 4a, 4e, 5a, 6a, and Supplementary Fig. 3, 6, 15a, 16 using Rhinoceros 3D and KeyShot, and further arranged using Microsoft PowerPoint (Microsoft Corporation).

Data Availability

The data supporting the findings of this study are available within the paper and its Supplementary Information files. Source data underlying the graphs and plots presented in the figures are provided with this paper. Additional data related to this study are available from the corresponding authors upon request. Requests for data will typically be responded to within two weeks, and the data will remain available for at least three years following publication.

Code Availability

All custom codes used for data processing, analysis, and simulation in this study are provided with this paper as Source Code files.

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Author contribution

J. B. A. and K. P. contributed equally to this work. J. B. A., K. P., and I. S. L. conceived the idea and designed the experiments. J. B. A. and K. P. performed the experiments and characterization. S. L. performed simulation. H. G. P. and J. M. L. performed array patterning. N. S. H, K. K., and K. P. performed characterization of array. Y. S. H. and S. H. P. performed visualization. J. H., S. K. P, and H. J. K. provided comments during the experiment. J. B. A. and K. P. drafted the manuscript.

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Competing interests

The authors declare no competing interests.

Additional information

Supplementary information is provided.

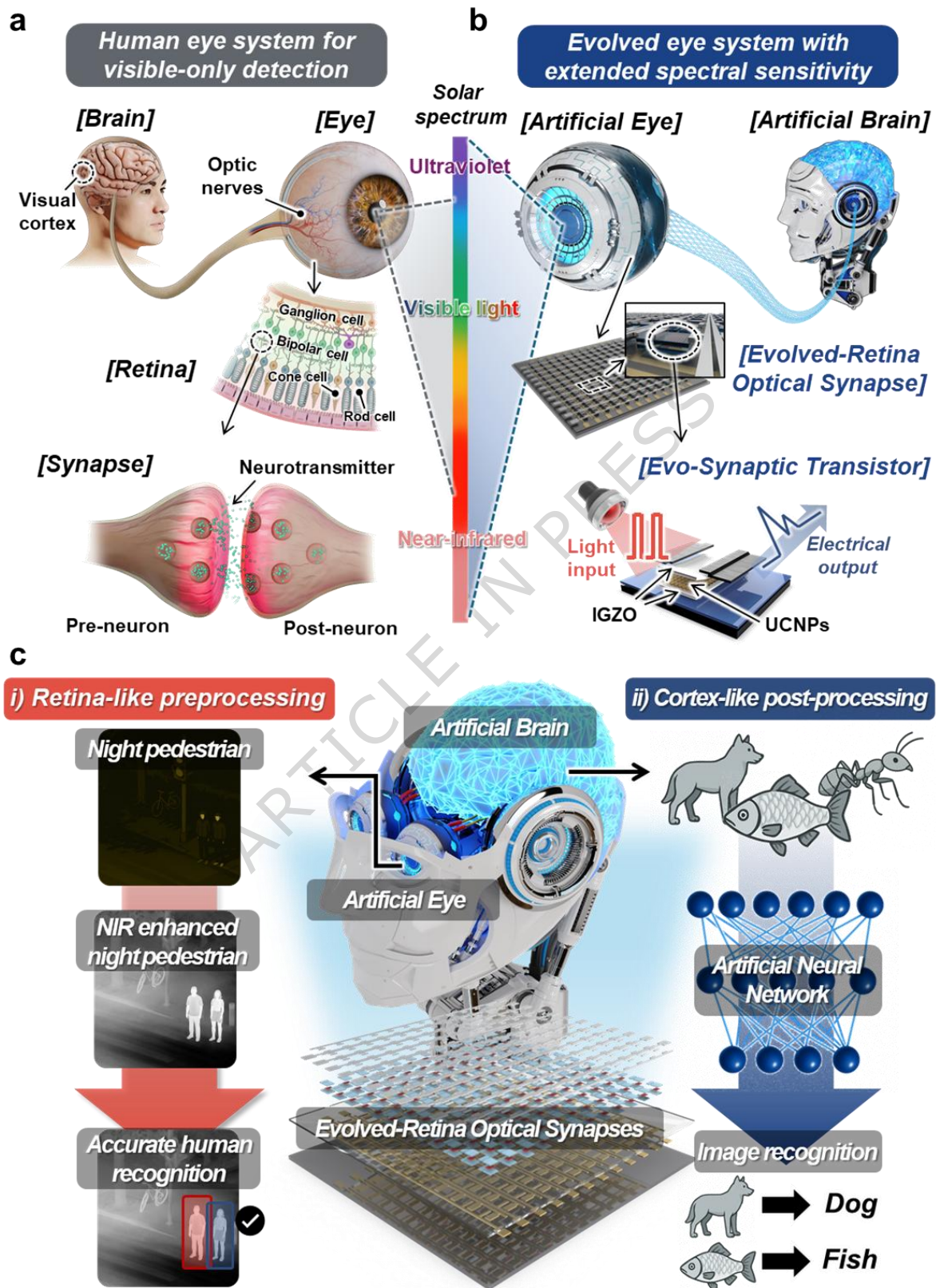


Fig. 1. Conceptual illustration of the retinocortical neuromorphic vision system with broadband perception and integrated in-sensor computing. Comparison between **a**, the biological human visual system, which is limited to visible light detection, and **b**, the proposed evolved artificial eye system with extended spectral sensitivity into the NIR region via the EROS and upconversion-assisted Evo-SynT. **c**, Conceptual framework of the full retinocortical architecture, in which the EROS array performs both (i) image preprocessing through NIR-based enhancement and (ii) post-processing classification through neural network-assisted object recognition, mimicking retinal and cortical functions respectively.

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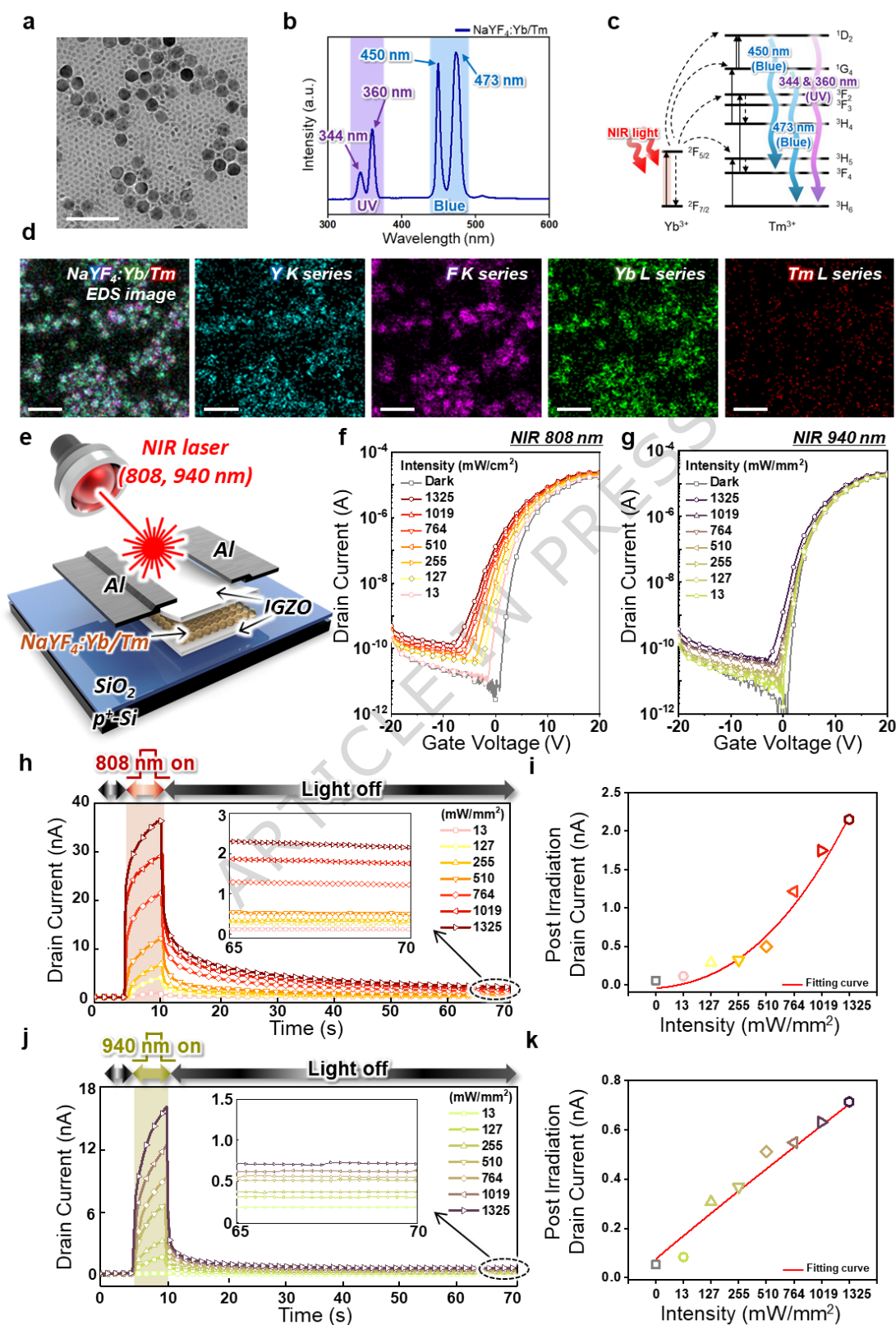


Fig. 2. Structural, compositional, and optoelectronic characterization of the upconversion-assisted Evo-SynT. **a**, TEM image of NaYF₄:Yb/Tm nanoparticles. Scale bar, 100 nm. **b**, Upconversion photoluminescence spectra of NaYF₄:Yb/Tm under 980 nm excitation. **c**, Schematic illustration of energy transfer and emission mechanism under NIR illumination. **d**, EDS elemental mapping images showing distribution of Na, Y, F, Yb, and Tm in the upconversion nanoparticles. Scale bar, 100 nm. **e**, Schematic of the Evo-SynT device incorporating a NaYF₄:Yb/Tm layer between two IGZO channel layers. Transfer curves of the Evo-SynT under NIR illumination at **f**, 808 nm and **g**, 940 nm. Time-dependent synaptic current responses of the Evo-SynT under **h**, 808 nm and **j**, 940 nm NIR illumination, where light was applied for 5 s at varying power intensities ranging from 13 to 1325 mW mm⁻². (Insets in **h** and **j** show enlarged views of the drain current levels measured from 65 s to 70 s.) Extracted PSC values at 70 s as a function of optical intensity under **i**, 808 nm and **k**, 940 nm NIR illumination.

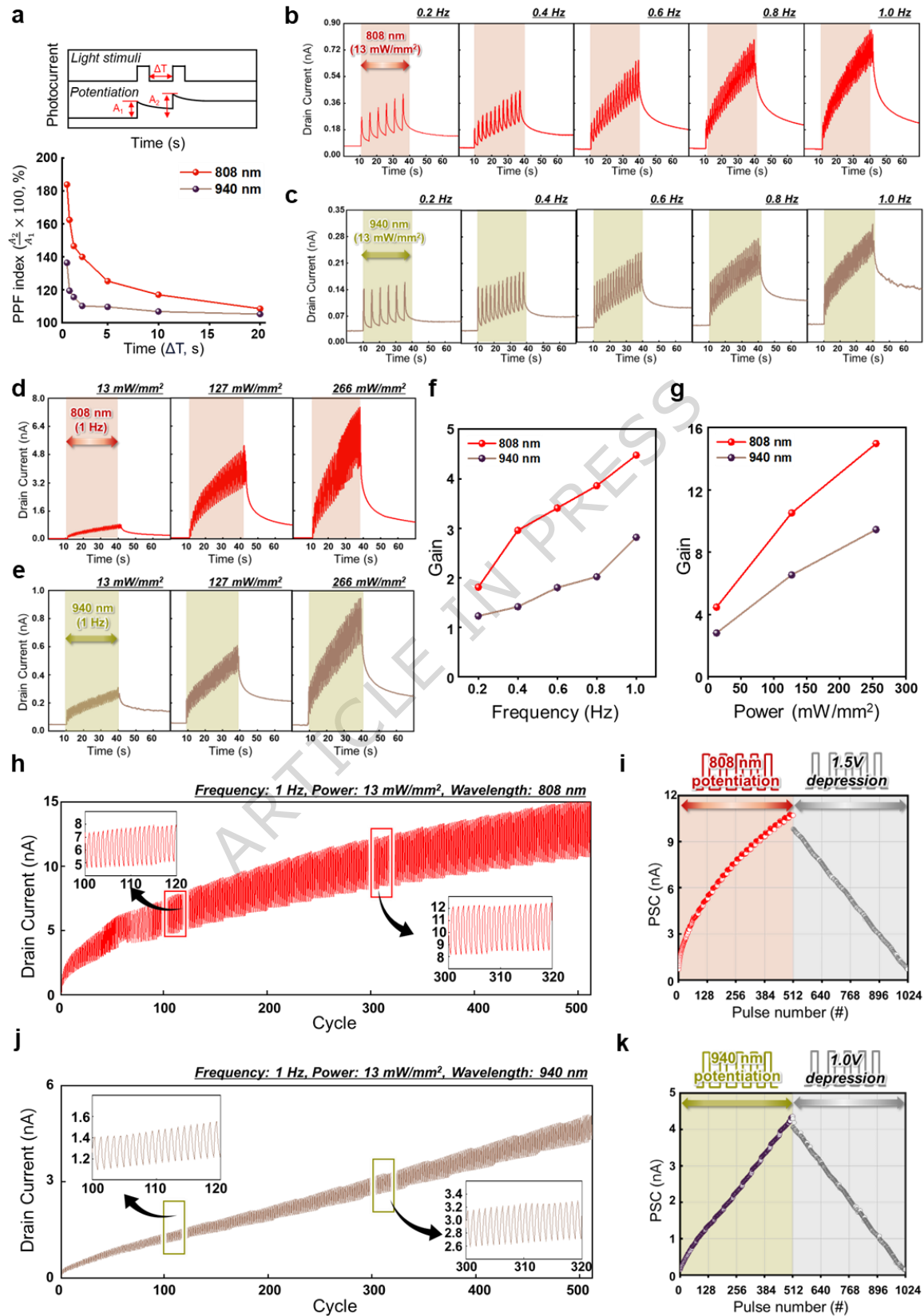


Fig. 3. Synaptic functionality of Evo-SynT under NIR illumination. **a**, PPF behavior under 808 nm and 940 nm NIR illumination. Dynamic postsynaptic current evolution under increasing pulse frequency (0.2 to 1 Hz) at fixed power (13 mW mm^{-2}), showing frequency-dependent synaptic strengthening at **b**, 808 nm and **c**, 940 nm. Pulse intensity–dependent synaptic behavior at fixed frequency (1 Hz), with PSC increasing with power (13 to 266 mW mm^{-2}) under **d**, 808 nm and **e**, 940 nm. Corresponding gain (A_n/A_1) in PSC under **f**, 808 nm and **g**, 940 nm. Repetitive potentiation dynamics under 512 pulses at 13 mW mm^{-2} and 1 Hz under **h**, 808 nm and **j**, 940 nm. (Insets in **h** and **j** show enlarged views of the drain current measured from 100 s to 120 s and 300 s to 320s.) Bidirectional PSC modulation using optical potentiation followed by electrical depression, with symmetric conductance tuning achieved under **i**, 808 nm/1.5 V and **k**, 940 nm/1.0 V.

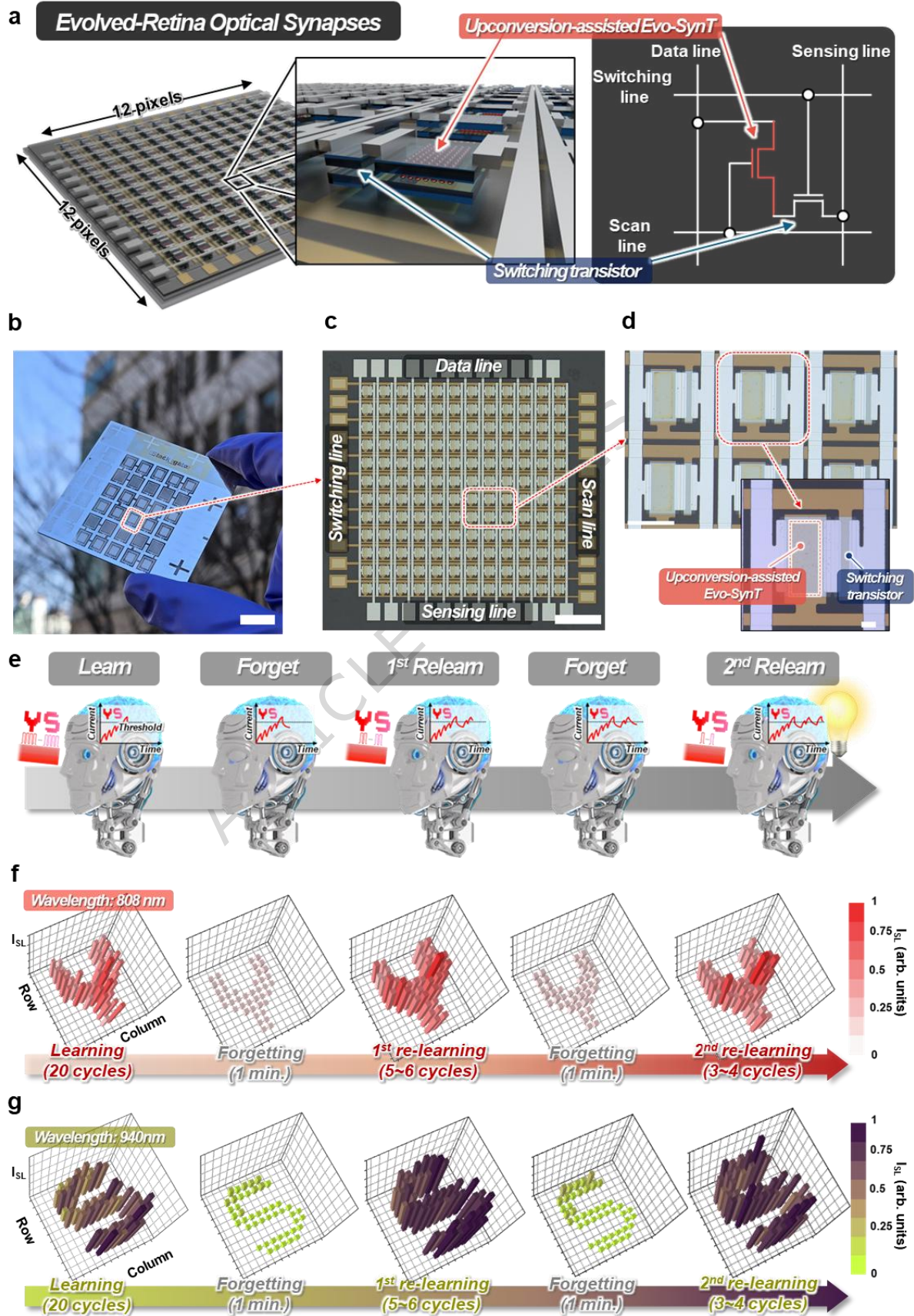


Fig. 4. Evo-SynT-based EROS arrays for NIR-Responsive In-Sensor Neuromorphic Vision Platforms. **a**, Schematic of the 12×12-pixel EROS array composed of upconversion-assisted Evo-SynTs and IGZO-based switching transistors in a 2T-per-pixel configuration. **b**, Photograph of the fabricated EROS array on glass substrate (scale bar, 1 cm), **c**, digital microscope image of the 12×12-pixel matrix layout (scale bar, 500 μm), and **d**, high-magnification view of a single pixel (top scale bar, 100 μm , bottom scale bar, 20 μm). **e**, Schematic of the learn–forget–relearn protocol mimicking biological memory encoding, erasure, and reactivation, performed using letter-shaped optical inputs under 808 nm and 940 nm NIR illumination. 3D plots of I_{SL} mapping across EROS pixels encoding the letter **f**, “Y” under 808 nm and **g**, “S” under 940 nm illumination.

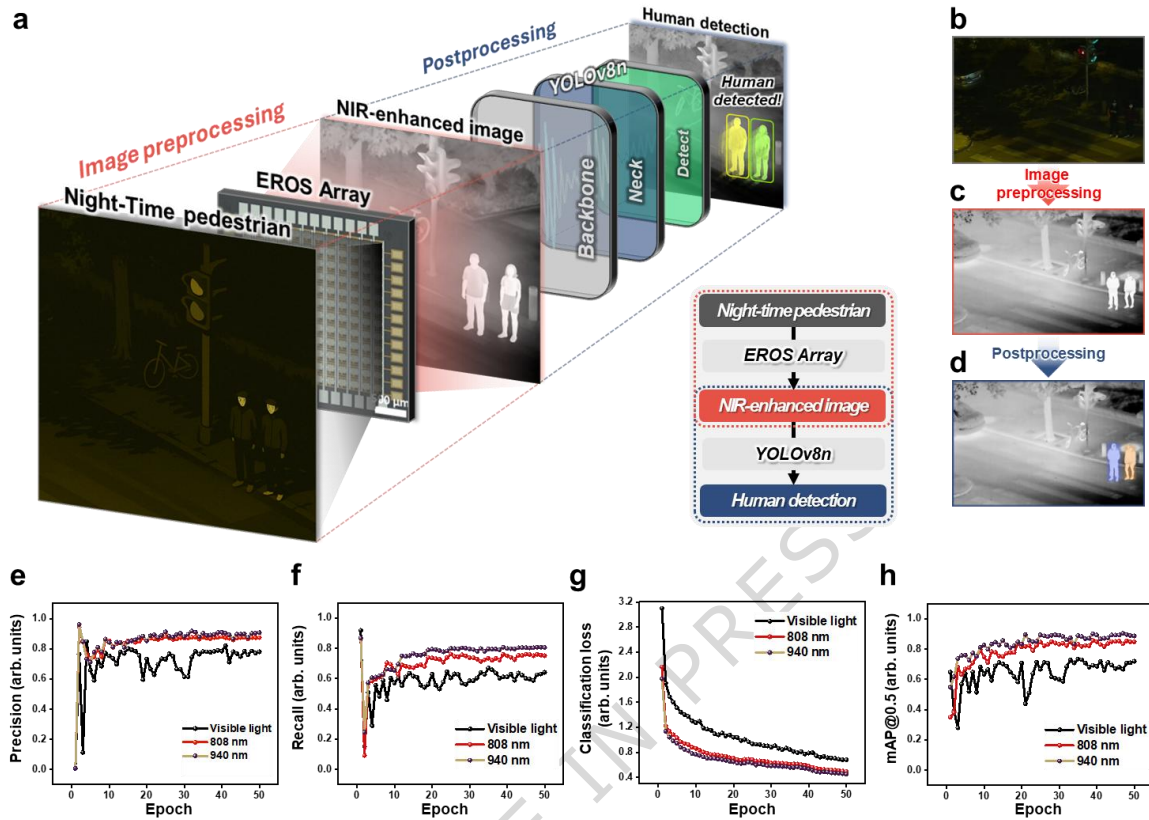


Fig. 5. In-sensor NIR preprocessing and post-sensor object detection enabled by EROS array for enhanced night vision. **a**, Schematic workflow of the neuromorphic vision pipeline: night-time pedestrian images are enhanced through in-sensor NIR pre-processing using the EROS array, followed by post-sensor classification with a YOLOv8n-based neural network. **b**, Raw input image of a pedestrian scene captured under visible-light conditions at night, where visual details are barely recognizable. **c**, NIR-enhanced image generated by the EROS array under 808 nm and 940 nm illumination, demonstrating improved visibility and contrast. **d**, AI-based human detection result obtained by feeding the EROS-enhanced image into the YOLOv8n object detection framework. Comparison of model performance metrics across different input modes—visible-only, 808 nm-enhanced, and 940 nm-enhanced images—over training epochs: **e**, precision, **f**, recall, **g**, classification loss, and **h**, mean average precision at IoU threshold 0.5.

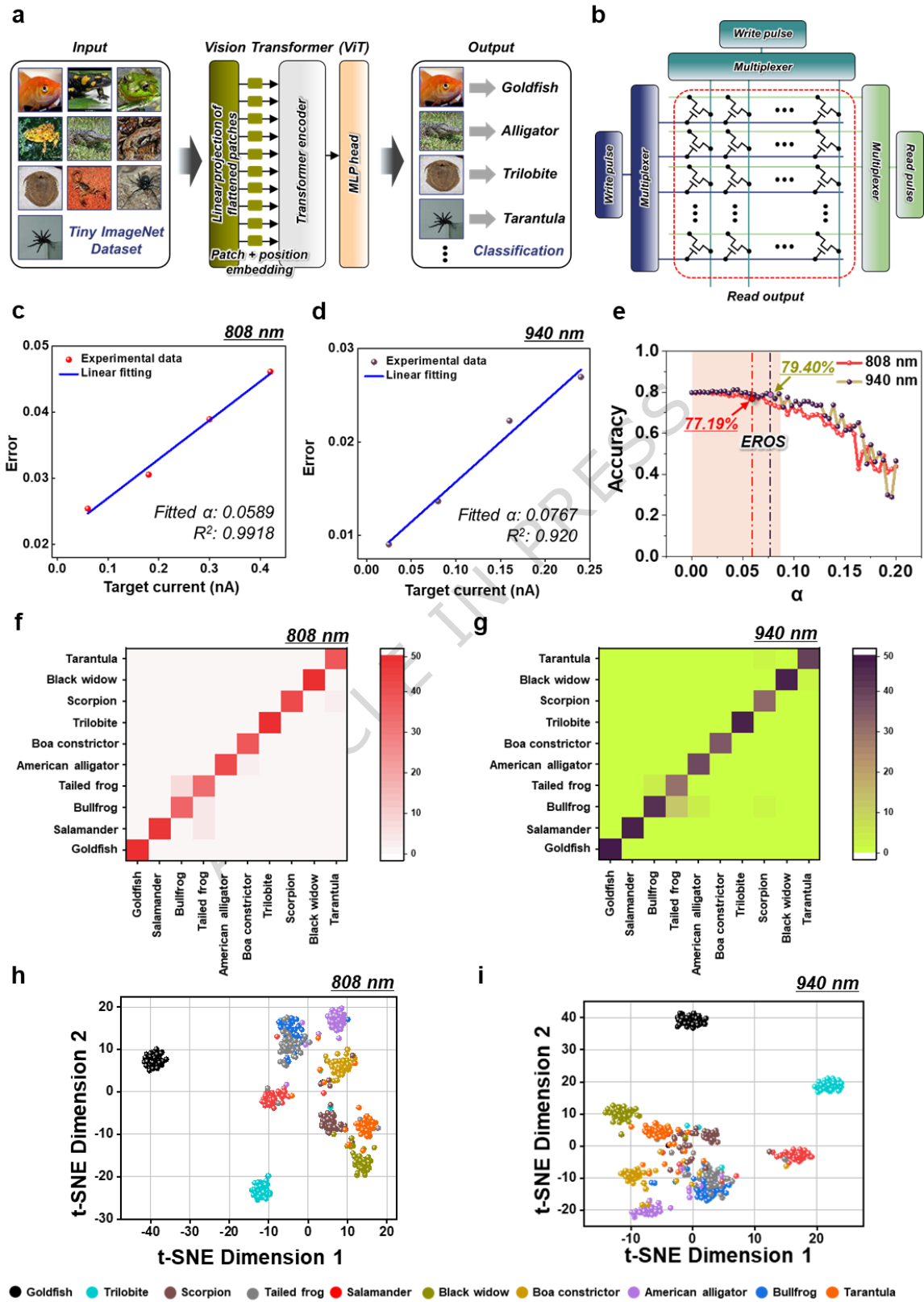


Fig. 6. Post-process neuromorphic classification using EROS-derived synaptic weights integrated into a ViT model. **a**, Schematic of the ViT-based image classification pipeline on Tiny ImageNet. **b**, Schematic of the MLP head incorporating EROS-based synaptic weights, enabling analog in-memory computation in the transformer architecture. Linear fitting of synaptic programming error versus target state current under **c**, 808 nm and **d**, 940 nm illumination. **e**, Classification accuracy versus error coefficient α . Confusion matrices generated from ViT models trained with EROS-derived synaptic weights under **f**, 808 nm and **g**, 940 nm. t-SNE visualizations of class-specific embedding distributions under **h**, 808 nm and **i**, 940 nm.

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Editor's summary:

Current artificial vision systems are less effective beyond the visible spectrum. Here, An et al. report an oxide-semiconductor-based vision platform that enables direct near-infrared signal detection, reliable image enhancement and subsequent image processing under low-light conditions.

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