

Scalable TCNQ-Doped Graphene Oxide Sensor for Neuromorphic Machine Vision

Xinyu HUANG^{1†}, Jihong WANG^{2†}, Lin WANG^{1†}, Hao SHI^{1,3}, Wenting JIAO¹,
Tangjie MU¹, Yang GAO¹, Menglai ZHANG¹, Lei ZHANG^{1*},
Junchao REN^{3*}, Kun YIN¹, Hui YU¹, and Yong WANG^{3*}

¹Zhejiang Lab, Hangzhou 311100, China

²Key Laboratory of Smart Manufacturing in Energy Chemical Process, Ministry of Education of the People's Republic of China, East China University of Science and Technology, Shanghai 200237, China

³Shanghai Advanced Research Institute, Chinese Academy of Sciences, Shanghai 201210, China

[†]These authors contributed equally to this work and should be considered co-first authors

*Corresponding authors: Lei ZHANG, E-mails: zhanglei2438@zhejianglab.org,
Junchao REN, and renjc@sari.ac.cn, and
Yong WANG wangyong@sari.ac.cn

Abstract: Neuromorphic machine vision systems have garnered substantial interest due to their potential for achieving autonomous control through real-time visual perception and processing. Two-dimensional materials offer a highly promising option for neuromorphic photodetectors due to their tunable electrical and optical properties, as well as their compatibility with heterogeneous integration. However, the fabrication of such devices often involves inefficient or expensive processes, limiting their widespread commercial adoption. To address these challenges, we develop a scalable 7,7,8,8-tetracyanoquinodimethane (TCNQ)-doped graphene oxide (p-GO) sensor by utilizing easily prepared graphene oxide as a substrate and employing a surface charge transfer doping strategy to modulate its charge state. This device exhibits a high and linearly tunable responsivity. By varying the applied bias voltage, the responsivity can be adjusted from 1.4 mA/W to 25 mA/W. With precise control over the photoelectric response at 76 levels, we establish a 3×3 array of p-GO sensors as programmable kernels for optical image edge processing and convolutional neural networks, achieving the impressive accuracy of up to 97.7% in letter recognition tasks. We anticipate that this work will significantly enhance the widespread adoption and commercial utilization of neuromorphic detectors.

Keywords: Neuromorphic machine vision; graphene oxide; programmable sensor arrays; convolutional neural networks

Citation: Xinyu HUANG, Jihong WANG, Lin WANG, Hao SHI, Wenting JIAO, Tangjie MU, *et al.*, "Scalable TCNQ-Doped Graphene Oxide Sensor for Neuromorphic Machine Vision," *Photonic Sensors*, 2026, 16(2): 9560013.

1. Introduction

Machine vision plays a crucial role in

autonomous driving, surveillance systems, robotics, and medical imaging applications [1–3]. As time-sensitive and data-intensive demands continue

Received: 8 November 2025 / Revised: 24 December 2025

©The author(s) 2026. Published by Tsinghua University Press. This is an open access article under the Creative Commons Attribution 4.0 International License (<http://creativecommons.org/licenses/by/4.0/>)

DOI: 10.26599/PhoS.2026.9560013

Article type: Research article



清华大学出版社
Tsinghua University Press

SciOpen

to grow, the conventional edge machine vision systems struggle to keep up with the increasing frame rates and pixel densities of modern sensors. This challenge is primarily due to the sequential processing limitations inherent in the von Neumann computing architecture [4–6]. When processing image data requires repetitive data conversion and transfer between physically separated functional components, such as sensory, computing, and memory units, it results in high energy consumption and increased latency. The human retina provides an elegant biological solution to these limitations. It contains diverse cell types, including photoreceptors (rods and cones), horizontal cells, bipolar cells, amacrine cells, and retinal ganglion cells, which serve functions such as detecting light, converting it into neurochemical signals, encoding stimulus properties, and providing homeostatic and metabolic support [7], as illustrated in Fig. 1(a). In contrast with the conventional edge machine vision systems, the human retina not only detects visual information but also processes it – performing tasks such as noise suppression and image sharpening – before transmitting the encoded data to the brain for further cognitive processing [7–10]. This dual functionality reduces redundancy and enhances the efficiency of information processing in the brain. Inspired by this mechanism, neuromorphic machine vision seeks to preprocess light signals directly within sensors, thereby reducing the burden of data transmission and the computational load on the downstream hardware. Consequently, photodetectors based on retina-inspired neuromorphic architectures have attracted widespread attention from researchers [11–15].

To realize the neuromorphic photodetector, it is critical to mimic the center-surround antagonistic receptive field in the biological retina by achieving adjustable ambipolar photoresponse in the individual device [16]. The unique properties of 2-dimensional (2D) materials make them ideal for this application, as their atomically thin layers allow for full

modulation of carriers by the applied electric field, without being affected by the screening effects typically observed in bulk materials [4, 17, 18]. With the advent of increasingly sophisticated comprehension on the underlying mechanisms, coupled with the development of novel structures such as Schottky barriers, p-n junctions, and metal-semiconductor-metal configurations [19], the 2D material (2DM)-based neuromorphic photodetectors have been proposed, which present remarkable characteristics including high mobility, high responsivity, and ultrathin profiles [20–25]. However, when it comes to devices based on the homogeneous material system, commonly employed 2DM fabrication techniques such as mechanical exfoliation and chemical vapor deposition confront pivotal challenges, including unpredictable flake thickness, diminutive domain sizes, and the necessity of expensive substrates [26–29]. Furthermore, the fabrication of multi-layered stacked structures for heterojunction or chemically unstable 2DMs presents an even more formidable undertaking [30]. Therefore, there is an urgent need to develop scalable and economical fabrication methods that can unlock the potential of 2DM-based neuromorphic photodetectors for massive production.

Here, we present a scalable 7,7,8,8-tetracyanoquinodimethane (TCNQ)-doped graphene oxide sensor for neuromorphic machine vision. Utilizing the refined Hummers method [31], we have successfully synthesized a large-area about the 1 cm×3 cm and high-quality graphene oxide (GO) film. To overcome the challenges related to the insulation properties and the limited light absorption of the GO, we employ a surface charge transfer doping strategy to regulate the GO charge-related properties, resulting in the formation of GO-organic π - π interfaces. This device demonstrates excellent photodetection performance, with the tunable photoresponsivity from 1.4 mA/W to 25 mA/W and the response time within 100 μ s. This device can be programmed to control the photoelectric response

precisely at distinguishable 76 levels, which is used to represent the weight parameters in matrix-vector multiplication (MVM) computation. We construct a 3×3 array of p-doped graphene oxide (p-GO) sensors, employing them as programmable kernels for optical image edge processing. It is worth noting that due to the high resistance characteristics of the GO material, detectors based on the GO do not

require patterning during array formation, which reduces the complexity of the fabrication process. Furthermore, based on this device, we demonstrate a convolutional neural network, achieving the impressive accuracy of up to 97.7% in letter recognition tasks. We envision that this work will contribute to the commercial applications of neuromorphic detectors.

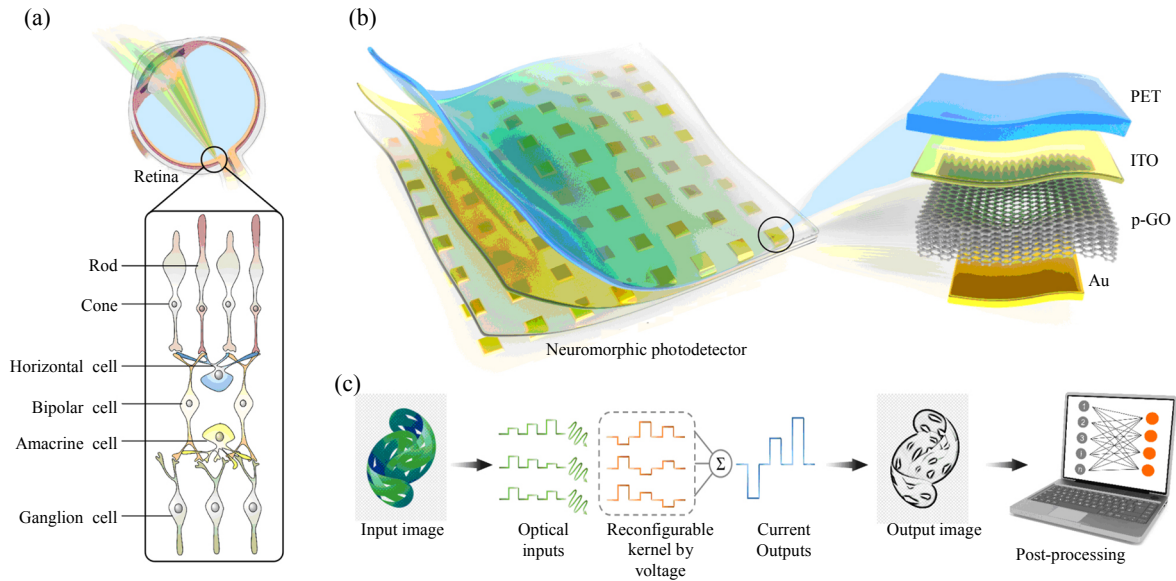


Fig. 1 Neuromorphic machine vision system: (a) the schematic illustration of the human visual system (the retina consists of various cells that can detect and process incident light), (b) the structure, and (c) the function diagram of the p-GO sensor array (PET: polyethylene terephthalate; ITO: indium tin oxide).

2. Results and discussion

2.1 Design and fabrication of the p-GO sensor

2.1.1 Design of the p-GO sensor

Inspired by the signal preprocessing function of the human retina, we design a neuromorphic photodetector based on the p-GO, as shown in Fig. 1(b). The device structure, from top to bottom, consists of a PET substrate, an ITO thin film, a p-GO layer, and Au electrodes. The p-GO layer generates the photocurrent under illumination, while the ITO and Au electrodes are used to apply a bias voltage. The PET substrate ensures optical transparency and provides mechanical flexibility. Notably, owing to the relatively high electrical resistance of the p-GO film, only the Au electrodes

need to be patterned into an array. The p-GO and ITO layers remain continuous, which simplifies the fabrication process and facilitates integration, as elaborated in later sections. By exploiting the voltage-dependent responsivity of the p-GO layer, the device can implement in-sensor computing. Images are projected as light signals onto the sensor array, and the bias voltages applied to individual pixels encode the responsivity matrix. The total photocurrent of the array thus represents a weighted sum of the inputs, realizing multiply-accumulate (MAC) operations [Fig. 1(c)]. In summary, the p-GO sensor combines structural simplicity, scalability, flexibility, and ease of fabrication, making it a promising platform for the neuromorphic vision hardware.

2.1.2 Preparation of the p-GO sensor

The functional layer of this detector consists of a p-doped GO film. Despite the ease of preparation for pure GO films, they exhibit notably weak photoresponse. To address the challenges associated with GO's insulation properties and limited light absorption, we employ a surface charge transfer doping strategy to modulate the charge-related properties of the GO. This strategy forms GO-organic π - π interfaces, markedly enhancing the device's overall performance. Figure 2(a) presents a schematic diagram illustrating the preparation process of p-GO films. The GO solution is synthesized from the natural graphite powder using a modified Hummers method [31]. The synthesized GO is then doped with the TCNQ, a p-type dopant, to improve the conductivity of the GO nanosheets. A flexible p-GO film is subsequently fabricated by depositing the doped GO solution onto ITO/PET substrates, followed by a controlled drying process. Further experimental details can be found in Supplementary files. In Fig. 2(b), a scanning electron microscopy (SEM) image showcases the morphology of the resulting p-GO film, which exhibits a distinctive pattern with typical sizes ranging from 2 μm to 5 μm on its surface. The surface flatness of the film is confirmed by atomic force microscopy (Fig. S1, Supplementary files). It's worth highlighting that the aforementioned preparation approach for p-GO films presents several advantages, including simplicity and cost-effectiveness. By utilizing a solution-based method, the synthesis process becomes relatively straightforward and accessible, making it an attractive option for researchers seeking an economical approach to fabricating p-GO films.

To gain deeper insights into the modifications induced by TCNQ doping, Raman spectroscopy is employed to elucidate its impact on the GO, as presented in Fig. 2(c). The Raman spectra of the GO display characteristic peaks at 1 597 cm^{-1} (G band) and 1 339 cm^{-1} (D band), corresponding to the

in-plane vibration of sp^2 carbon atoms and structural defects of the GO, respectively [32]. Upon incorporation of the TCNQ, the G band of the TCNQ-GO composite film shifts to 1 610 cm^{-1} , suggesting adsorption of the TCNQ on the GO surface or within interlayers, accompanied by effective p-type doping and charge transfer between the GO and the TCNQ [33]. The intensity ratio of the D band to the G band (I_D/I_G) decreases from 1.586 1 to 1.495 6, indicating a reduction in the defect density within the p-type GO composite. Additionally, two other bands are observed for the GO at 2 682 cm^{-1} (2D band) and 2 912 cm^{-1} (D+G band). The relatively low intensity of the 2D band implies a compact interlayer stacking, while the notable attenuation of the D+G band – associated with defect density – further corroborates the decreased defect concentration and enhanced interlayer adhesion in the composite film [34]. The p-doping effect induced by the TCNQ effectively mitigates structural defects in the GO, thereby promoting restoration of the delocalized π -conjugated network.

To further clarify the charge transfer mechanism at the TCNQ-GO interface, X-ray photoelectron spectroscopy (XPS) is performed. The deconvolution of the C 1s XPS peak of the p-GO composite film in Fig. 2(d) reveals that the carbon types are C–C/C=C, C–O, O=C–O [35], and C–N, confirming the successful incorporation of the TCNQ into the GO. Compared with the pristine GO [Fig. 2(e)], the relative abundances of C–C/C=C, C–O, and O=C–O/C=O bonds are substantially reduced in the composite film. This reduction results from the intercalation and adsorption of the TCNQ, which disrupts these native bonds and facilitates the formation of new C–N linkages. Concurrently, the decomposition of unstable oxygen-containing functional groups promotes restoration of the π -conjugated network within the GO, enhancing π - π interactions between the GO and TCNQ. Notably, the C–O and O=C–O/C=O peaks exhibit slight shifts

toward lower binding energies, indicating locally increased electron density around oxygen-containing species. This phenomenon originates from internal charge redistribution within the GO after electron transfer from the GO to the TCNQ [36]. Specifically, electrons are extracted from the carbon framework

of the GO by the strong electron accepting TCNQ, while nearby oxygen groups compensate for the electron-deficient regions, leading to reduced binding energies. These results further confirm the occurrence of charge transfer from the GO to the TCNQ, consistent with Raman spectroscopy evidence.

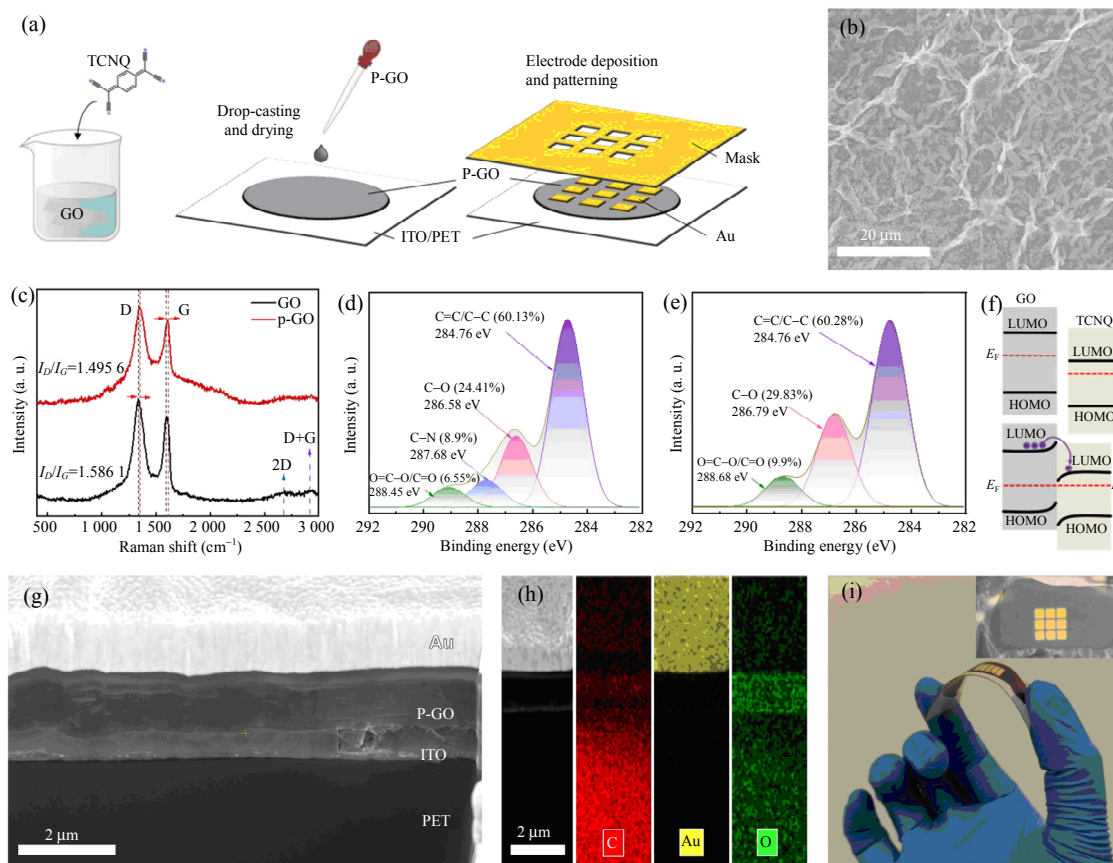


Fig. 2 Device fabrication and characterization: (a) schematic illustration describing the production process of the GO sensor array, (b) the SEM image of the p-GO film before depositing electrodes, (c) Raman spectra of the p-GO composite film, with the GO film as the control, C 1s XPS spectra of the p-GO composite film (d) and the GO film (e), respectively, (f) the energy arrangement diagram at the GO and TCNQ interfaces and interface charge transfer diagram (E_F is the Fermi level), (g) the SEM image of the section of the p-GO sensor, (h) elemental mapping of (g), and (i) the photograph of the flexible p-GO device (the inset shows the top view of the device).

Charge transfer doping via TCNQ introduction markedly enhances the electrical conductivity of the GO. The Fermi level (E_F) plays a central role in governing the electrical properties of the material. In this system, the disparity between the Fermi levels of the TCNQ and GO critically influences charge transport dynamics. As illustrated in Fig. 2(f), a proposed model depicts the charge transfer process at the GO-TCNQ interface. Owing to the deeply lying lowest unoccupied molecular orbital (LUMO)

of the TCNQ, electrons are extracted from the donor states of the GO. Upon contact, the energy level difference promotes electron transfer from the donor state of the GO to the LUMO-related acceptor state of the TCNQ. This redistribution of charges modifies the relative alignment of the Fermi levels, leading to the formation of a space charge region at the interface accompanied by charge accumulation and band bending. Graphene doping strategies include physical doping, chemical doping, and

structural modulation. Structural methods, such as folding or creating metamaterials, can tune electronic and optical properties [37] but often require complex processes. Chemical doping, e.g., atomic substitution or molecular adsorption, mainly introduces extra carriers to modulate conductivity [38]. In contrast, our physical surface doping uses non-covalent molecular adsorption and work function differences to induce charge transfer, avoiding complex chemistry or high-vacuum equipment. This approach effectively tunes the GO carrier concentration while offering simplicity and scalability.

Sensor arrays are subsequently constructed using the doped p-GO films as the functional layer. The array device exhibits a typical sandwich structure composed of PET/ITO/p-GO/Au layers, as depicted in the final step in Fig. 2(a). The gold electrode array on the p-GO thin film is deposited by magnetron sputtering with a hard mask. A cross-sectional SEM image is shown in Fig. 2(g). It reveals that the ITO layer has a thickness of 100 nm, the p-GO film has a thickness of 1.8 μm , and the gold electrode has a thickness of 1.2 μm . It is noteworthy that the microstructural features observed in the cross-sectional SEM images, including bright strips and localized breaks in the ITO layer and continuous light stripes in the p-GO layer, arise from the sample preparation method rather than intrinsic material properties. A cryogenic fracturing technique is employed, wherein samples are embrittled in liquid nitrogen and mechanically fractured. The brittle nature of the ITO layer and the layered structure of the GO lead to irregular fracture surfaces and stepped edges, which appear as bright features under SEM imaging. These localized artifacts do not affect the uniformity or functional properties of the device. In order to validate the outcomes of the layered device fabrication, a cross-sectional analysis is performed using energy dispersive spectroscopy (EDS), as shown in Fig. 2(h). The results indicate

the presence of carbon (C) and oxygen (O) in both the p-GO and PET regions, consistent with the expected chemical composition of the GO. In addition, Au signals are clearly detected in the metal pad region, verifying the designed layer configuration and the accuracy of the fabrication process. Together with the cross-sectional SEM observations, the EDS analysis provides a comprehensive characterization of the device, confirming the chemical composition of individual regions and the successful realization of the intended multilayer structure with the desired material distributions and thicknesses.

The inset shown in Fig. 2(i) showcases a representative 3×3 sensor array. Within this array, each square gold pad measures 2 mm on each side, with a separation distance of 1 mm between adjacent pads. The overall dimensions of the device span approximately 1 cm in width and 3 cm in length. The bent configuration of the device is clearly depicted in Fig. 2(i), highlighting its flexibility and conformability to curved surfaces. In this work, the p-GO sensor array is fabricated at the centimeter scale to demonstrate a novel and scalable manufacturing paradigm for neuromorphic vision sensors. Leveraging the high lateral resistance of the p-GO film, functional arrays can be formed by patterning only the top electrodes, simplifying the fabrication process, and avoiding potential damage to the active layer. This approach lays a solid foundation for future miniaturization, where higher integration density can be realized by transitioning from the shadow-mask electrode fabrication to standard photolithography. A uniform gold film can first be deposited on the p-GO layer, followed by high-resolution photolithography and etching to create a dense electrode array. This mature process can achieve micron- and sub-micron-scale features, offering a feasible path toward the high integration density required for advanced applications while preserving the scalability demonstrated here.

2.2 Characterization and operation of the p-GO device

2.2.1 Optical and electrical response of the p-GO device

We experimentally quantify the photoresponse of individual sensors. The experimental procedure involves irradiating the PET side of the device using a laser with a wavelength of 405 nm, and subsequently applying voltage and measuring current through the Au and ITO electrodes. The incident laser intensity can be tuned by the variable optical attenuator. Figure 3(a) shows the I - V characteristics of the sensor with the laser intensities ranging from 5 mW to 50 mW. At a fixed light intensity, the device exhibits near linear current response. The linear current response across a wide voltage range provides a foundation for encoding weights of the kernel for in-sensor computing. The photoconductance of the device increases with the increment of light intensity. As the light intensity rises from 5 mW to 50 mW, the photoconductance increases from 0.96 μ S to 1.44 μ S. To further validate the linear relationship between the photocurrent and light intensity, we measure the curves of photocurrent variation with light intensity at different voltages, as illustrated in Fig. 3(b). Across the range from 0 V to +14 V, the photocurrent exhibits a near linearity with the growth of light intensity. While higher laser powers may introduce nonlinearity due to Joule heating, the data collected under our experimental conditions show excellent linearity, with R -squared values exceeding 0.99 in Fig. 3(b). Therefore, within the measured range, the photocurrent can be considered approximately linear, and the device operates stably under the laser intensities used for image encoding. By analyzing the device's response to light and voltage, the photocurrent can be described as $I = \beta P V$, where P represents the incident light intensity, βP corresponds to the light-induced conductance, β is the proportionality coefficient, and V is the applied

voltage. Therefore, the photocurrent change induced by light is directly proportional to both the light intensity and the applied voltage, enabling precise modulation through these two parameters. Due to the high lateral resistance of the p-GO material, only the area of the electrode pad directly illuminated by the laser contributes to the photocurrent. Therefore, when calculating the responsivity, it is necessary to account for the ratio between the laser spot area and the electrode pad area, rather than using the total laser power (for a detailed calculation process, see Supplementary files S1.2). Based on the photocurrent measurements for a single pad, the responsivity of the p-GO detector ranges from 1.4 mA/W to 25 mA/W, depending on the applied bias voltage. The photoresponse characteristics of the p-GO photodetector are systematically evaluated as a function of the TCNQ mass ratio, as shown in Fig. 3(c). The photocurrent increases monotonically with the higher TCNQ loading, consistent with a charge-transfer-mediated mechanism. Notably, an optimal doping concentration of the 0.5 wt% TCNQ is identified, achieving a favorable balance among the enhanced photoresponse, suppressed dark current, and material economy, thereby maintaining overall device performance.

To investigate the photoresponse time of the device, we measure the switching behavior under typical operating conditions with the bias voltage of 4 V and illumination power of 30 mW. The temporal photoresponse is shown in Fig. 3(d). During the transition from dark to illuminated conditions, the current increases rapidly. The measured rising edge (10% to 90%) is 41 μ s, while the falling edge (90% to 10%) is 55 μ s. Both the rising and falling edge response time is below 100 μ s, satisfying the requirements for modern industrial vision sensor applications. The detector response time is fundamentally limited by the intrinsic dynamics of the GO film, which can be further optimized by adjusting the applied bias and the degree of molecular doping. Applying a higher bias can

enhance the carrier drift, thereby accelerating the rise and decay speeds. In addition, using dopants with the stronger electron-withdrawing ability, such as the TCNQ, can facilitate more efficient charge transfer, further improving the response speed. By

combining these strategies, the p-GO sensor's response time could be further reduced while retaining useful responsivity, ensuring its suitability for high-speed and real-time neuromorphic vision applications.

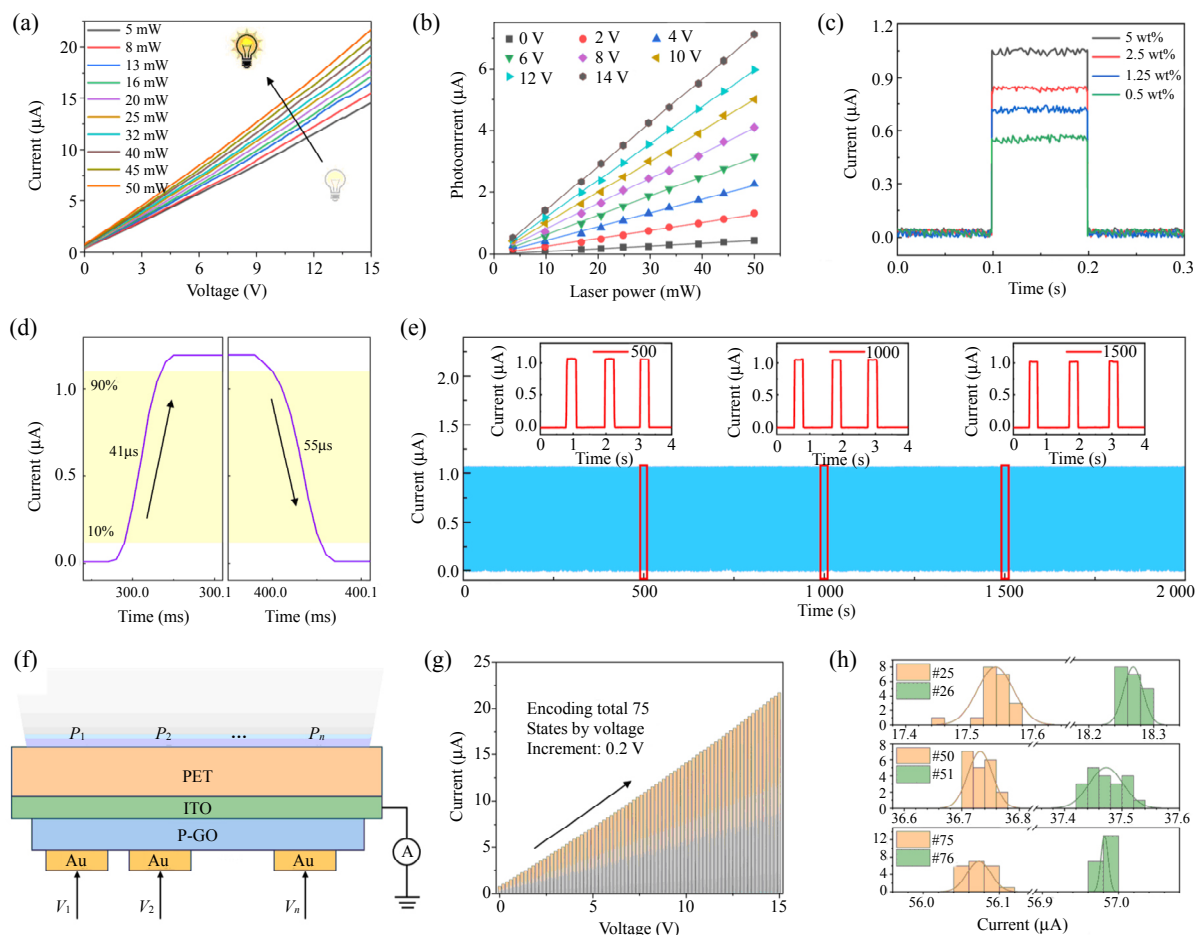


Fig. 3 Device response: (a) the I - V characteristics of the p-GO sensor under varied light intensity, (b) the photocurrent at different bias voltages (scatter) and their linear fit (solid line), (c) monitoring the current of the p-GO photodetector at different mass ratios of the TCNQ under a 405 nm illumination, (d) the photoresponse time and recovery time of the p-GO device under 405 nm illumination, (e) the long-term cyclic stability of the photodetector (the insets indicate the magnified areas around 500 cycles, 1 000 cycles, and 2 000 cycles, respectively. Insets are enlarged plots corresponding to the three regions enclosed by the red square), (f) the schematic diagram of the p-GO sensor array for the working mechanism, (g) the discrete voltages and corresponding current for in-sensor computing, and (h) the reproducibility of the photocurrent for 3 pairs of adjacent states, and the legends show the state number.

The p-GO photodetector exhibits both excellent operational durability and fabrication reproducibility. Under an illumination power of 30 mW and a bias voltage of 4 V, over 2 000 cyclic photoresponse tests show no noticeable degradation in either photocurrent amplitude or response time [Fig. 3(e)]. To assess fabrication reproducibility, ten independently prepared p-GO photodetectors from different batches are systematically evaluated. The

devices exhibit the highly consistent photocurrent and responsivity under identical illumination (Fig. S3, Supplementary files). These results confirm the excellent stability and reliability of the solution-processed fabrication process.

Table 1 compares the performance of our sensor with that of typical 2DM-based photodetectors. Our device has a significant advantage in terms of area. Traditional devices based on 2DMs typically

use mechanical exfoliation to prepare the light-absorbing layer [1, 20, 39, 40], resulting in device sizes on the order of tens of micrometers. Alternative methods like magnetron sputtering [41, 42] and pulsed laser deposition (PLD) [43] can produce devices with sizes ranging from millimeters to centimeters. Additionally, ultrasonic deposition methods [44] can achieve millimeter-scale sizes. In contrast, the drop-casting method used in our study can easily achieve wafer-scale sizes on the order of centimeters. Besides, when compared to other fabrication methods, our device stands out for its simplicity and low cost. Mechanical exfoliation requires manual operation, which is not conducive to large-scale production, and the shape of the devices is also difficult to control. Magnetron sputtering or PLD requires large-scale equipment and must be performed in a vacuum chamber [41–43], making the overall process quite complex. The liquid metal-based synthesis method needs to be carried out at high temperatures [45]. In contrast,

our device fabrication is carried out in a solution, with the final steps being drop-casting and annealing, eliminating the need for the large-scale equipment. Furthermore, our device can be easily arrayed. Typically, arraying sensors requires patterning both the photosensitive material and the electrodes, whereas our material, due to its high resistance, only requires the electrode array to enable multiple sensor units to work simultaneously and automatically sum the current. This will be discussed in more detail in the next section. This feature not only reduces the complexity of the fabrication process but also minimizes the risk of compromising material stability due to the introduction of other substances during lithography and etching, such as oxidation or unintended chemical reactions. In addition to the aforementioned advantages, our device's responsivity of 1.4 mA/W–25 mA/W is comparable to that of other notable photodetectors and even exceeds some. Finally, our refined measurements demonstrate that the device exhibits rise and fall time

Table 1 Comparison of neuromorphic photodetectors based on 2DMs.

Ref.	Year	Main material	Preparation method	Area	Thickness	Responsivity (mA/W)	Rising/falling time	Arraying
This work	2025	P-GO	Drop-casting	1×3 cm ²	2 μm	1.4 to 25	41 μs/55 μs	Electrodes
[1]	2020	WSe ₂	Mechanically exfoliated	70×120 μm ²	4 nm	−60 to +60	Within 50 ns	—
[20]	2022	Black phosphorus	Mechanically exfoliated	20×30 μm ²	11 nm	2 to 65	—	—
[39]	2020	MoS ₂ /Si	Mechanically exfoliation	10×10 μm ²	4 nm	19	178 μs/198 μs	—
[40]	2014	Rhodamine 6G/MoS ₂	Mechanically exfoliation	6.25×13 μm ²	0.6 nm	1.38	5.1 μs/2.3 s	—
[41]	2019	Amorphous-MoS ₂	Magnetron sputtering	5×5 mm ²	43 nm	47.5	10 ms/16 ms	Photosensitive material and electrodes
[43]	2018	MoS _{2.15}	Pulsed laser deposition	Φ 20 mm	167 nm	21.8	—	
[42]	2018	WS ₂ /Si	Magnetron sputtering	1 cm ²	42 nm to 300 nm	4	40 μs	—
[44]	2022	MoS ₂ -xOx	Ultrasonic deposition	1×1 mm ²	200 nm	0.003 to 5.1	—	—
[45]	2023	β-In ₂ Se ₃ /MoS ₂	Liquid metal-based synthesis method	125 μm ²	1 nm	—	50 ms	—
[46]	2016	MoS ₂ /graphene	LPCVD	1×1.5 cm ²	1.45 nm	32	2.3 s	—
[47]	2020	β-In ₂ Se ₃ /MoS ₂	CVD	50 μm ²	<10 nm	3.16	52 ms/57 ms	—
[48]	2023	NbS ₂ /MoS ₂	CVD	10×20 μm ²	1.8 nm	7 to 1 000	304 ms	Photosensitive material and electrodes

of 41 μs and 55 μs , respectively, which represent an advanced level of performance. In summary, the responsivity of our device is comparable to that of notable studies, and our device boasts a far simpler fabrication process and a significantly larger area, by 5 orders–6 orders of magnitude.

2.2.2 Mechanism of operation

Figure 3(f) provides a comprehensive insight into the operational mechanism of the device. The P-GO film absorbs the incident light through the PET/ITO, producing electron-hole pairs. The density of these pairs exhibits a positive correlation with the incident light intensity under the experimental conditions. A bias voltage is applied between the Au electrodes and ITO ground, guiding the directional movement of electrons and facilitating the generation of the photocurrent. A noteworthy aspect of the device's design is the negligible leakage current among the sensor units. This remarkable feature is attributed to the substantial resistance of the graphene oxide material. Experimental measurements reveal a vertical resistance of 1.8 M Ω between the Au electrode and ITO. Impressively, when considering two positions with a horizontal spacing of 0.4 μm , the resistance significantly increases to 20 M Ω . This pronounced resistance anisotropy effectively suppresses leakage currents, indicating that there is the potential for further reduction of the pixel area. Such scaling could enable miniaturized pixel architectures without compromising isolation between the sensor units. The key factors for further pixel miniaturization lie in optimizing the fabrication resolution and signal-to-noise ratio (SNR), rather than limitations of the material itself. Future efforts will focus on improving doping uniformity and adopting advanced photolithography techniques in place of shadow-mask processes. These strategies are expected to realize finer pixel structures and higher integration density, while maintaining the excellent optoelectronic performance of p-GO devices.

Utilizing the optical and electrical response of individual sensors, weight matrices can be encoded into the sensor array. Each sensor exhibits different light responsivities at various voltages, resulting in distinct photocurrents under the same light intensity but different voltages. The calibration process of the programmable p-GO sensor array is highly efficient and automated. Owing to the linear current-voltage characteristics under constant illumination [Fig. 3(a)], the photoresponsivity scales proportionally with the bias voltage, allowing the V - R relationship of each pixel to be determined by only two measurement points. Consequently, the entire 3×3 array can be calibrated within minutes, while the required data volume is minimal and can be permanently stored and reused. Figure 3(g) illustrates the varied photocurrent responses obtained by encoding different voltages for the device under a constant light intensity of 45 mW. The voltage range spans from 0 V to 15 V, divided into 76 states with a voltage interval of 0.2 V between adjacent states. The number of divisible states directly determines the adjustment precision of the weights, thereby influencing the precision of the computation. The minimum photocurrent interval is about 0.3 μA . The consistency before and after the repeated loading of weights is a crucial factor affecting the accuracy of neuromorphic detector computations. To verify the distinctiveness and repeatability of voltage encoding weights, we select 3 pairs of adjacent states, repetitively apply the voltages, and analyze the statistical results in Fig. 3(h). With the 20 times weight loading for each state, the standard deviation of the current is consistently below 0.03 μA for all 6 states, meeting the requirement for state separation. For a Gaussian distribution function, the full width at half maximum (FWHM) is approximately 2.35 times the standard deviation. Therefore, a standard below 0.03 μA corresponds to the FWHM of no more than 0.07 μA , which aligns with the visual assessment shown in Fig. 3(h). We further conduct measurements on

more states, obtaining similar results (Fig. S4, Supplementary files). The photocurrent responses exhibit excellent repeatability, meeting the requirements for state separation. These results confirm that the calibrated weight values can be stably reused over long periods, effectively reducing operational overhead and ensuring the practicality of the neuromorphic vision system for real-world applications. The experimental results demonstrate that the sensor can support analog computation or achieve 6-bit precision digital computation.

2.3 In-sensor convolution in the p-GO device

An important application of the neuromorphic detector is image convolution processing, such as image sharpening and edge extraction. In this work, the detector array serves both signal detection and convolution calculation functions. To process image inputs, the pixel grayscale values are encoded into optical intensities (P_i). The encoding leverages the linear photoresponse of the p-GO sensor, ensuring that each pixel's optical power is directly proportional to its normalized grayscale value, thereby providing a precise and reproducible mapping from digital image information to analog optical stimuli: $P_i = P_{\min} + G_i(P_{\max} - P_{\min})$, where G_i is the normalized grayscale value of the pixel i , and $P_{\min}$ and $P_{\max}$ are the minimum and maximum optical intensities. The laser output, controlled by a variable optical attenuator (VOA), is programmed according to this mapping to achieve the target light intensity for each sensor unit. Subsequently, the mapped optical intensity (P_i) is applied to each pixel using a reflective spatial light modulator. The array is configured by assigning specific voltages to each pixel through a 64-channel voltage source, effectively programming the photoresponsivity (R_i) of each sensor to implement a convolution kernel. After the optical input, the total photocurrent $I = \sum (R_i \cdot P_i)$ is measured, corresponding to a multiply-accumulate (MAC) operation that represents the processed pixel value. For the

purpose of image processing, we select four kernels

matrices as examples, including $\begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$

for bottom edge detection, $\begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$ for left

edge detection, $\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$ for sharpen, and

$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$ for motion blur. These matrices are

designed to perform specific convolution operations on the input images, allowing for various image manipulation and feature extraction tasks.

The results of the image processing are illustrated in Fig. 4. For our experiments, we utilize three grayscale cartoon images with an 8-bit depth: greeting, query, and travelling. The dimensions of the greeting and query images are 258×258 pixels, while the travelling image has a larger size of 1185×1185 pixels. In our methodology, the grayscale value of each pixel in the input images is employed to encode the corresponding light intensity. The light intensity is adjusted by modulating the laser output intensity continuously and then input into the sensor array. By analyzing the resulting photocurrent outputs, we obtain the processed images that undergo the convolution operation. We compare the experimental results with theoretical calculations and observe that they exhibit a closely matching trend (Figs. S5–S7 and Table S1, Supplementary files). As shown in Fig. 4, the application of bottom Sobel and left Sobel kernels effectively emphasizes lower and left edges, respectively, while alternative Sobel matrices can enhance upper and right edges. This approach is valuable for recognizing edge features in images. Furthermore, the utilization of sharpening and motion blurring kernels produces distinct effects on

processed images. These techniques are essential for edge feature recognition in the field of image processing. When comparing different images, it can be observed that the edge-enhancement effect for the travelling image appears visually different from the greeting and query images. This originates from the relative scale between the convolutional kernel and the image resolution: in the 258×258 -pixels images, the 3×3 kernel corresponds to a relatively large receptive field, leading to stronger visual contrast, whereas in the 1185×1185 -pixels image the same kernel corresponds to a much smaller

receptive field, capturing finer structures and producing more localized and detailed edge features. Thus, the variation reflects a resolution-dependent scaling effect that is consistent with the convolution theory and highlights the versatility of the device in processing images across resolutions. For practical applications involving images of different sizes, tailoring the kernel scale or device design to achieve an appropriate receptive field can further optimize performance, underscoring the potential of adaptive kernel-device co-design strategies in neuromorphic image processing.

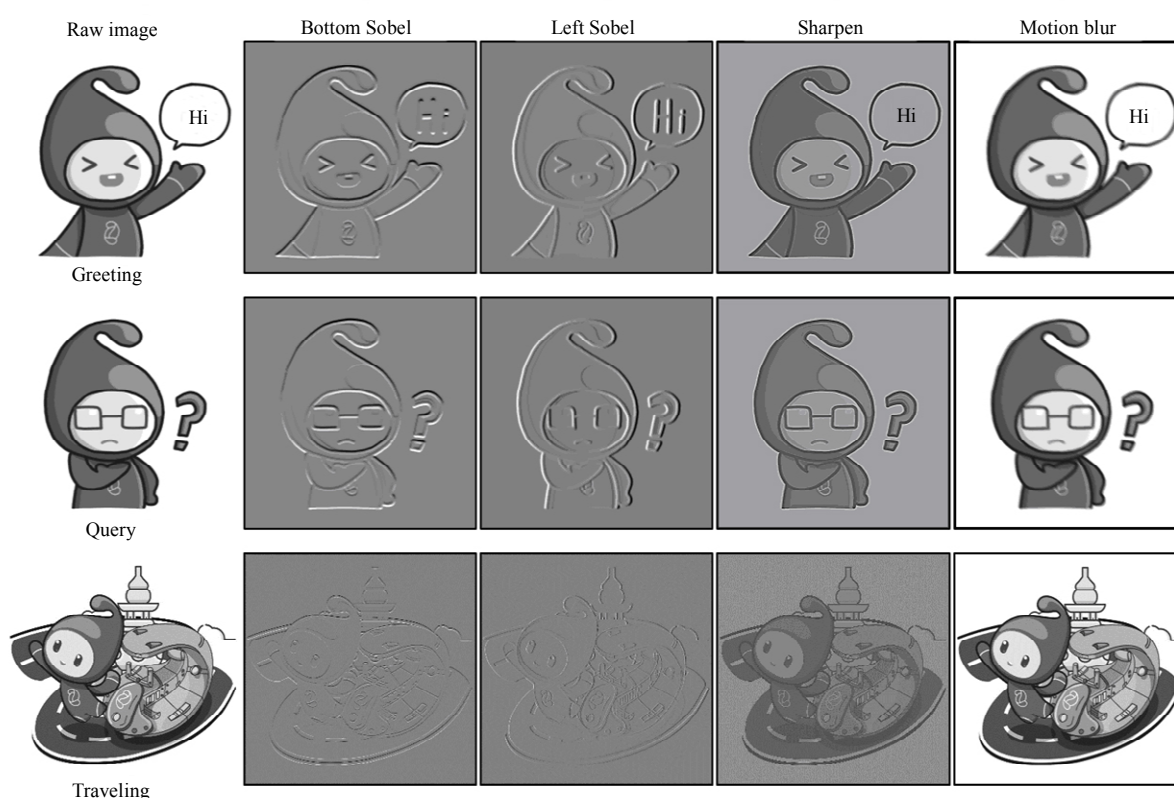


Fig. 4 Image convolution with in-sensor computing. Three original images and their convolving results by four kernels including bottom Sobel, left Sobel, sharpen, and motion blur. Top: greeting (258×258 pixels); middle: query (258×258 pixels); low: traveling (1185×1185 pixels).

By performing in-sensor analog MAC operations directly at the point of photon detection, the p-GO sensor array inherently integrates sensing and computation, effectively bypassing the conventional “sense-digitize-transmit-process” pipeline used in traditional digital imaging systems. This direct integration not only simplifies the processing

workflow but also substantially reduces energy dissipation, resulting in ultra-low static power consumption. Experimental measurements indicate that each channel consumes only $\sim 8 \mu\text{W}$ (4 V and $2 \mu\text{A}$), and for the entire 3×3 array, the total static power remains below $72 \mu\text{W}$. The exceptionally low power is primarily attributed to the passive electrical

nature of the p-GO core and the elimination of intermediate conversion and amplification steps, as the first-layer computation is performed inherently during photon detection. To quantitatively assess the energy efficiency of this approach, a representative 3×3 Sobel operator is applied to a 258×258 -pixel image, yielding a total energy consumption of 52.4 mJ. This evaluation highlights the advantage of merging photodetection and initial convolutional computation within the sensor array, in contrast to the conventional digital pipelines, which incur additional energy overhead from continuous pixel readout, frame digitization, and subsequent computation in separate processors. Overall, the p-GO sensor array demonstrates a highly energy-efficient paradigm for edge vision processing, combining the ultra-low static power with scalable analog computation, which is particularly advantageous for always-on neuromorphic applications.

2.4 In-sensor CNN for image recognition

The MAC operation characteristics of the GO sensor array mentioned above suggest that these devices are capable of serving as image classifiers in the convolutional neural network (CNN). To demonstrate this, we fabricate a 3×3 sensor array and established a CNN for the purpose of recognizing letters “Z”, “J”, and “L”. The Gaussian noise with different standard deviations ($\sigma=0.1, 0.2, 0.3, 0.4$, and 0.5) is randomly added to three original letters, resulting in letter images with various levels of noise, as depicted in Fig. 5(a). These letter images, along with their corresponding noise levels, are then split into separate training and test datasets. In Fig. 5(b), the CNN architecture consists of an input layer that detects a 5×5 -pixel image, followed by a convolutional layer comprising three 3×3 convolutional kernels, and a 27×3 fully connected (FC) layer. The convolutional kernels are loaded onto the device using voltage signals. Each pixel of the input image is encoded into optical intensity, allowing the device to illuminate each pixel

accordingly. The device then performs sequential convolution operations with these three kernels, resulting in a total of 27 photocurrent outputs. These photocurrents are subsequently fed into the FC layer in the computer, where they contribute to the generation of three output values for label determination.

The dependence of classification accuracy on epochs is presented in Fig. 5(d). For σ values ranging from 0.1 to 0.4, the accuracy quickly reaches 100% after 16 epochs. Figure 5(c) shows the values in the kernel 1 for $\sigma=0.5$ after 40 epochs. In the case of the test datasets with $\sigma=0.5$, the accuracy near 98% is achieved after 40 epochs. The variation evolution for the three classifier neurons (f_1, f_2, f_3) in each epoch is presented in Fig. 5(e). For all “Z”, “J”, and “L” images, the target image can be well distinguished from all three labels, which demonstrates the successful recognition. Utilizing these kernels, the simulated and experimental results for $\sigma=0.5$ are summarized in the confusion matrices in Fig. 5(f). The p-GO based CNN reaches the accuracy of 97.7%, comparable with the simulated results obtained from a computer (96.6%). To further assess the performance boundaries and generalization capabilities of the p-GO sensor-based CNN, we conduct additional simulative analyses under higher and previously untested noise levels. While the CNN achieves high accuracy (97.7%) for the Gaussian noise within $\sigma=0.1$ to 0.5 for the letter recognition task (classes “Z”, “J”, and “L” in 5×5 -pixel images), simulating with higher noise levels ($\sigma=0.6$ to 0.9) shows a gradual decrease in classification accuracy (Fig. S8, Supplementary files). Specifically, at $\sigma=0.6$, the accuracy decreases to 92.6%, and at $\sigma=0.9$, it drops to 82.0%. This reduction reflects the inherent limitation of the model’s generalization beyond its trained noise range, rather than any deficiency of the p-GO sensor hardware. Importantly, the sensor array continues to perform precise and programmable MAC operations

with linear photoresponse and reliable weight encoding. These results indicate that while the hardware remains fully functional, the overall system-level performance is governed by the

algorithm's trained operational domain, underscoring the need for potential future exploration of noise-resilient network architectures to extend robust classification capabilities.

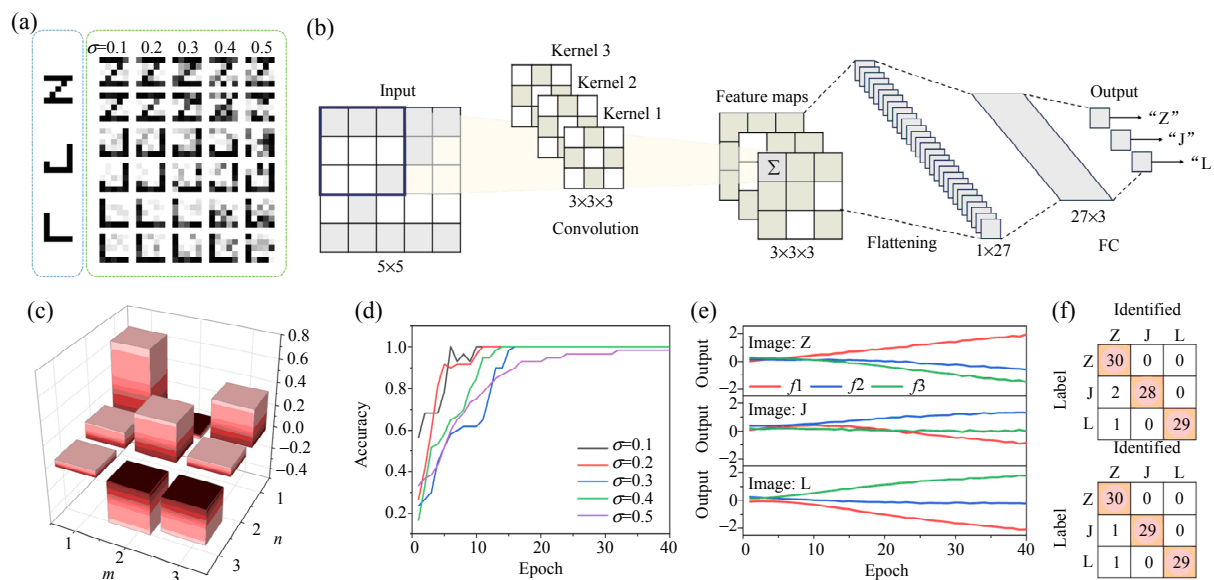


Fig. 5 GO sensor array for classification tasks: (a) 5×5 images of letters “Z”, “J”, and “L”, and examples of their variants with the random Gaussian noise $\sigma=0.1$ to 0.5, (b) schematic diagram of the CNN for image classification based on the GO sensor array, (c) the weight value of the kernel 1 after 40 epochs for $\sigma=0.1$ (row and column indexes are labeled m and n), (d) classification accuracy of the classifier during training for datasets with different noise levels, (e) evolution for the three classifier neurons f_1, f_2 , and f_3 in 40 epochs for images with a noise level of $\sigma=0.1$, and (f) the simulated (top) and experimental (bottom) confusion matrices for 90 images from the test dataset (colored diagonal elements in the table indicate the correctly identified cases).

3. Conclusions

We have presented a scalable TCNQ-doped GO sensor designed for neuromorphic machine vision. Through the implementation of the refined Hummers method and p-type doping, we successfully synthesize a large-area and high-quality p-GO film. The device exhibits excellent photodetection performance. With precise control over the photoelectric response, we have established an array of p-GO sensors as programmable kernels for optical image edge processing and convolutional neural networks, achieving the impressive accuracy of up to 97.7% in letter recognition tasks. Our work highlights the significant application value of TCNQ-doped graphene oxide films in neuromorphic detectors. Furthermore, the integration of ultrathin and flexible characteristics in this device holds the great potential for expanding the application of

artificial vision systems. With the potential for real-time processing and reduced latency, the device is expected to find applications in diverse fields, such as smart home systems, wearable health monitoring devices, and LiDAR in autonomous vehicles. We anticipate that this research will significantly contribute to the widespread production and commercial application of neuromorphic detectors.

Supplementary files

The supplementary files can be downloaded from the webpage of this article in *Photonic Sensors* (<https://www.sciopen.com/journal/1674-9251>).

Acknowledgment

This work was supported by the National Key Research and Development Program of China (Grant No. 2022YFB2901000), the Science and

Technology Program of Zhejiang, China (Grant No. 2025C01043), the National Natural Science Foundation of China (Grant No. 12204436), the Zhejiang Provincial Natural Science Foundation of China (Grant No. LQ24A040011), the Postdoctoral Fellowship Program of China Postdoctoral Science Foundation (Grant No. GZC20252242), the National Natural Science Foundation of China (Grant No. 12305362), and the National Key Research & Development Program of China (Grant No. 2021YFA1601003). The authors thank the Nano Fabrication Center of Zhejiang Laboratory for device fabrication and characterization and the Shiyanjia Laboratory (www.shiyanjia.com) for the XPS test.

Declarations

Conflict of Interest The authors declare that they have no competing interests.

Permissions All the included figures, tables, or text passages that have already been published elsewhere have obtained the permission from the copyright owner(s) for both the print and online format.

Open Access This article is distributed under the terms of the Creative Commons Attribution 4.0 International License (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution, and reproduction in any medium, provided you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license, and indicate if changes were made.

Use of AI Statement None.

References

- [1] L. Mennel, J. Symonowicz, S. Wachter, D. K. Polyushkin, A. J. Molina-Mendoza, and T. Mueller, “Ultrafast machine vision with 2D material neural network image sensors,” *Nature*, 2020, 579(7797): 62–66.
- [2] T. Wang, M. M. Sohoni, L. G. Wright, M. M. Stein, S. Y. Ma, T. Onodera, *et al.*, “Image sensing with multilayer nonlinear optical neural networks,” *Nature Photonics*, 2023, 17(5): 408–415.
- [3] Z. Zhang, S. Wang, C. Liu, R. Xie, W. Hu, and P. Zhou, “All-in-one twodimensional retinomorphic hardware device for motion detection and recognition,” *Nature Nanotechnology*, 2022, 17(1): 27–32.
- [4] C. Liu, H. Chen, S. Wang, Q. Liu, Y. G. Jiang, D. W. Zhang, *et al.*, “Two-dimensional materials for next-generation computing technologies,” *Nature Nanotechnology*, 2020, 15(7): 545–557.
- [5] Y. Shen, N. C. Harris, S. Skirlo, M. Prabhu, T. Baehr-Jones, M. Hochberg, *et al.*, “Deep learning with coherent nanophotonic circuits,” *Nature Photonics*, 2017, 11(7): 441–446.
- [6] D. Ielmini and H. S. P. Wong, “In-memory computing with resistive switching devices,” *Nature Electronics*, 2018, 1(6): 333–343.
- [7] T. Euler, S. Haverkamp, T. Schubert, and T. Baden, “Retinal bipolar cells: elementary building blocks of vision,” *Nature Reviews Neuroscience*, 2014, 15(8): 507–519.
- [8] J. K. Song, J. Kim, J. Yoon, J. H. Koo, H. Jung, K. Kang, *et al.*, “Stretchable colour-sensitive quantum dot nanocomposites for shape-tunable multiplexed phototransistor arrays,” *Nature Nanotechnology*, 2022, 17(8): 849–856.
- [9] N. D. Shemonski, F. A. South, Y. Z. Liu, S. G. Adie, P. S. Carney, and S. A. Boppart, “Computational high-resolution optical imaging of the living human retina,” *Nature Photonics*, 2015, 9(7): 440–443.
- [10] H. Wässle, “Parallel processing in the mammalian retina,” *Nature Reviews Neuroscience*, 2004, 5: 747–757.
- [11] G. X. Zhang, Z. C. Zhang, X. D. Chen, L. Kang, Y. Li, *et al.*, “Broadband sensory networks with locally stored responsivities for neuromorphic machine vision,” *Science Advances*, 2023, 9(37): 5104.
- [12] B. Dang, K. Liu, X. Wu, Z. Yang, L. Xu, Y. Yang, *et al.*, “Onephoto transistor-one memristor array with high-linearity light-tunable weight for optic neuromorphic computing,” *Advanced Materials*, 2023, 35(37): 2204844.
- [13] N. Ilyas, J. Wang, C. Li, D. Li, H. Fu, and D. Gu, “Nanostructured materials and architectures for advanced optoelectronic synaptic devices,” *Advanced Functional Materials*, 2021, 32(15): 2110976.
- [14] S. Kwon, S. W. Cho, M. Kim, J. Heo, Y. Kim, and S. Park, “Environment-adaptable artificial visual perception behaviors using a light-adjustable optoelectronic neuromorphic device array,” *Advanced Materials*, 2019, 31(52): 1906433.
- [15] D. Ghezzi, M. Antognazza, M. Maschio, E. Lanzarini, F. Benfenati, and G. Lanzani, “A hybrid bioorganic interface for neuronal photoactivation,” *Nature Communications*, 2011, 2(1): 166.
- [16] Y. Wu, W. J. Deng, X. T. Wang, W. J. Yu, Z. J. Chen, X. Q. Chen, *et al.* “Progress in bioinspired photodetectors design for visual information processing,” *Advanced Functional Materials*, 2023, 33(40): 2302899.
- [17] M. Chhowalla, D. Jena, and H. Zhang, “Two-

- dimensional semiconductors for transistors,” *Nature Reviews Materials*, 2016, 1(11): 1–15.
- [18] P. Cudazzo, I. Tokatly, and A. Rubio, “Dielectric screening in two-dimensional insulators: implications for excitonic and impurity states in graphene,” *Physical Review B*, 2011, 84: 085406.
- [19] Q. Ma, G. Ren, A. Mitchell, and J. Z. Ou, “Recent advances on hybrid integration of 2D materials on integrated optics platforms,” *Nanophotonics*, 2020, 9(8): 2191–2214.
- [20] S. Lee, R. Peng, C. Wu, and M. Li, “Programmable black phosphorus image sensor for broadband optoelectronic edge computing,” *Nature Communications*, 2022, 13(1): 1485.
- [21] H. Jang, C. Liu, H. Hinton, M. H. Lee, H. Kim, and M. Seol, “An atomically thin optoelectronic machine vision processor,” *Advanced Materials*, 2020, 32(36): 2002431.
- [22] F. Liao, Z. Zhou, B. J. Kim, J. Chen, J. Wang, T. Wan, *et al.*, “Bioinspired in-sensor visual adaptation for accurate perception,” *Nature Electronics*, 2022, 5(2): 84–91.
- [23] T. Ahmed, M. Tahir, M. X. Low, Y. Ren, S. A. Tawfik, E. L. Mayes, *et al.*, “Fully light-controlled memory and neuromorphic computation in layered black phosphorus,” *Advanced Materials*, 2021, 33(10): 2004207.
- [24] D. Kwak, D. K. Polyushkin, and T. Mueller, “In-sensor computing using a MoS₂ photodetector with programmable spectral responsivity,” *Nature Communications*, 2023, 14(1): 4264.
- [25] T. X. Li, J. S. Miao, X. Fu, B. Song, B. Cai, X. Ge, *et al.*, “Reconfigurable, non-volatile neuromorphic photovoltaics,” *Nature Nanotechnology*, 2023, 18(11): 1303–1310.
- [26] Y. Liu, N. O. Weiss, X. Duan, H. C. Cheng, Y. Huang, and X. Duan, “Van der waals heterostructures and devices,” *Nature Reviews Materials*, 2016, 1(9): 1–17.
- [27] W. Yu, K. Gong, Y. Li, B. Ding, L. Li, Y. Xu, *et al.*, “Flexible 2D materials beyond graphene: synthesis, properties, and applications,” *Small*, 2022, 18(14): 2105383.
- [28] T. Zhao, J. Guo, T. Li, Z. Wang, M. Peng, F. Zhong, *et al.*, “Substrate engineering for wafer-scale two-dimensional material growth: strategies, mechanisms, and perspectives,” *Chemical Society Reviews*, 2023, 52(5): 1650–1671.
- [29] Y. Saito, K. Shin, K. Terayama, S. Desai, M. Onga, Y. Nakagawa, *et al.*, “Deep-learning-based quality filtering of mechanically exfoliated 2D crystals,” *npj Computational Materials*, 2019, 5(1): 124.
- [30] J. D. Wood, S. A. Wells, D. Jariwala, K. S. Chen, E. Cho, V. K. Sangwan, *et al.*, “Effective passivation of exfoliated black phosphorus transistors against ambient degradation,” *Nano Letters*, 2014, 14(12): 6964–6970.
- [31] W. S. Hummers Jr. and R. E. Offeman, “Preparation of graphitic oxide,” *Journal of the American Chemical Society*, 1958, 80(6): 1339–1339.
- [32] J. Y. Wu, H. Lin, D. J. Moss, K. P. Loh, and B. H. Jia, “Graphene oxide for photonics, electronics and optoelectronics,” *Nature Reviews Chemistry*, 2023, 7(3): 162–183.
- [33] Y. Y. Rong, M. J. Large, M. Tripathi, S. P. Ogilvie, A. A. Graf, B. Y. Mao, *et al.*, “Charge transfer hybrids of graphene oxide and the intrinsically microporous polymer PIM-1,” *ACS Applied Materials & Interfaces*, 2019, 11(34): 31191–31199.
- [34] M. S. Seehra, V. Narang, U. K. Geddam, and A. B. Stefaniak, “Correlation between X-ray diffraction and Raman spectra of 16 commercial graphene-based materials and their resulting classification,” *Carbon*, 2017, 111: 380–385.
- [35] E. Husamelden and H. Fan, “Fluorinated functionalization of graphene oxide and its role as a reinforcement in epoxy composites,” *Journal of Polymer Research*, 2019, 26(2): 1–12.
- [36] Y. K. Li, L. Wang, F. Zhang, W. T. Zhang, G. S. Shao, and P. Zhang, “Detecting and quantifying wavelength-dependent electrons transfer in heterostructure catalyst via in situ irradiation XPS,” *Advanced Science*, 2023, 10(4): 2205020.
- [37] T. Tan, Z. Y. Yuan, H. Zhang, G. F. Yan, S. Y. Zhou, N. An, *et al.*, “Multispecies and individual gas molecule detection using Stokes solitons in a graphene over-modal microresonator,” *Nature Communications*, 2021, 12(1): 6716.
- [38] C. B. Bie, H. G. Yu, B. Cheng, W. K. Ho, J. J. Fan, J. G. Yu, “Design, fabrication, and mechanism of nitrogen-doped graphenebased photocatalyst,” *Advanced Materials*, 2021, 33(9): 2003521.
- [39] J. X. Guo, S. D. Li, Y. Z. Ke, Z. C. Lei, Y. Liu, L. N. Mao, *et al.*, “Broadband photodetector based on vertically stage-like MoS₂/Si heterostructure with ultra-high sensitivity and fast response speed,” *Scripta Materialia*, 2020, 176: 1–6.
- [40] S. H. Yu, Y. B. Lee, S. K. Jang, J. Y. Kang, J. Jeon, C. G. Lee, *et al.*, “Dye-sensitized MoS₂ photodetector with enhanced spectral photoresponse,” *ACS Nano*, 2014, 8(8): 8285–8291.
- [41] Z. Z. Huang, T. F. Zhang, J. K. Liu, L. H. Zhang, Y. H. Jin, J. P. Wang, *et al.*, “Amorphous MoS₂ photodetector with ultra-broadband response,” *ACS Applied Electronic Materials*, 2019, 1(7): 1314–1321.
- [42] H. S. Kim, M. Patel, J. D. Kim, and M. S. Jeong, “Growth of wafer-scale standing layers of WS₂ for self-biased high-speed UV-visible-NIR optoelectronic devices,” *ACS Applied Materials & Interfaces*, 2018, 10(4): 3964–3974.
- [43] Y. Xie, F. Liang, D. Wang, S. M. Chi, H. H. Yu, Z. S. Lin, *et al.*, “Room-temperature ultrabroadband photodetection with MoS₂ by electronic-structure

- engineering strategy,” *Advanced Materials*, 2018, 30(50): 1804858.
- [44] L. Pi, P. Wang, S. J. Liang, P. Luo, H. Wang, D. Li, *et al.*, “Broadband convolutional processing using band-alignment-tunable heterostructures,” *Nature Electronics*, 2022, 5(4): 248–254.
- [45] T. Ahmed, A. Jannat, V. Krishnamurthi, T. Aung, A. Mazumder, A. Zavabeti, *et al.*, “Atomically thin synaptic devices for optoelectronic neuromorphic vision,” *Advanced Materials Technologies*, 2023, 8(9): 2201772.
- [46] C. M. Chen, Z. H. Feng, Y. Y. Feng, Y. C. Yue, C. Q. Qin, D. H. Zhang, *et al.*, “Large-scale synthesis of a uniform film of bilayer MoS₂ on graphene for 2D heterostructure phototransistors,” *ACS Applied Materials & Interfaces*, 2016, 8(29): 19004–19011.
- [47] Z. X. Zou, D. Li, J. W. Liang, X. H. Zhang, H. W. Liu, C. G. Zhu, *et al.*, “Epitaxial synthesis of ultrathin β -In₂Se₃/MoS₂ heterostructures with high visible/near-infrared photoresponse,” *Nanoscale*, 2020, 12(11): 6480–6488.
- [48] P. Y. Huang, B. Y. Jiang, H. J. Chen, J. Y. Xu, K. Wang, C. Y. Zhu, *et al.*, “Neuro-inspired optical sensor array for high-accuracy static image recognition and dynamic trace extraction,” *Nature Communications*, 2023, 14(1): 6736.