

PHYSICS

High-capacity directional information processor using all-optical multilayered neural networks

Guannan Wang¹, Xiaofei Zang^{1,2*}, Teng Zhang¹, Zhiyu Tan¹, Ziqing Guo¹, Yiming Zhu^{1,2*}, Xianzhong Chen^{3*}, Songlin Zhuang¹

We propose a directional-diffractive deep neural network (D-D²NN) by encoding the wave propagation direction into a D²NN, introducing a new degree of freedom and enable high-capacity information processing. The unprecedented capability of metasurfaces in controlling light propagation provides a new opportunity to realize such a D-D²NN. We propose and demonstrate a versatile D-D²NN using three spin-decoupled metasurfaces. Simultaneous control of geometric and propagation phases is used to realize direction-dependent functionality. High-capacity information processing is demonstrated by controlling the distances between neighboring metasurfaces. The efficacy of our approach is exemplified through the classification of digits and fashion products in two channels and the calculation-like function realized in four channels. Moreover, the proposed D-D²NN can divide rich information into multiple channels, enabling high-volume data encryption. The metasurface-enabled deep learning networks with versatile directional functionalities provide a flexible route toward massively parallel processing, pattern recognition, encryption, and artificial intelligence systems.

INTRODUCTION

All-optical information processing, which uses photons as information carriers and is widely regarded as one of the most promising candidates for modern computing systems (1, 2), offers unique advantages such as high-speed processing, low energy consumption, and massively parallel capabilities. Over the years, there has been a long-standing pursuit of controlling light by developing brain-like optical neural computing frameworks, including optical reservoir computing (3), spiking neural networks (4), Mach-Zehnder interferometer networks (5, 6), and diffractive deep neural network (D²NN) (7–9). Notably, D²NN consisting of cascaded diffractive layers have emerged as a free-space platform that can take advantage of deep learning algorithms to design diffractive surfaces with unprecedented capabilities in all-optical computational tasks and visual processing (10). Benefiting from the light-speed operation and power efficiency, a plethora of all-optical information processors such as image classifiers (11, 12), logic operations (13), imaging processors through diffusive media, and universal linear transformations (14, 15) have been achieved on the basis of D²NNs. Despite the notable advances of D²NN, there are growing demands for integrating multiple functions/applications into D²NN, promoting the development of D²NN with high-capacity information processing capability.

To enhance the function integration, the multiwavelength D²NNs have been proposed to process multiple tasks with multiple wavelengths. This is realized by training a variety of tasks at different wavelengths and encoding the required phase profiles into three-dimensional (3D) printing diffractive surfaces. Examples include the multiwavelength unidirectional imaging (16, 17), multiwavelength

complex field imaging (18), and multispectral all-optical information hiding-decoding system (19). However, these unique functions rely on the construction of 3D-printed diffractive surfaces, which are hindered by large volume, high cost, and low integration levels. Metasurfaces, 2D counterpart of metamaterials, can generate abrupt phase modulations at flat meta-atom interfaces, which provide an ultracompact platform to manipulate the properties of electromagnetic (EM) waves at subwavelength scale (20, 21). Because of the exotic properties of metasurfaces, a plethora of applications such as the generalized Snell's law of refraction/reflection (22, 23), spin-Hall effects (24), quantum sources (25, 26), holograms (27–29), polarization converters (30, 31), and metalens (32–34) have been demonstrated in recent years.

The dielectric metasurface has been designed on the basis of phase and wavelength multiplexing to integrate multitarget D²NN with different tasks operating at distinct wavelengths (35). Polarization, as a fundamental property of light, can be applied to design polarization-multiplexed D²NN that enables the capability in processing multiple tasks by switching the incident polarization states. Using a single diffractive network trained by deep learning, a polarization-multiplexing diffractive processor has been constructed to perform multiple complex-valued, arbitrary linear transformations (36). A metasurface-based polarization multiplexed all-optical linear neural network can be designed to process various recognition tasks including the recognition of handwritten digits and fashion items (37). To break the multiplexing between two orthogonal polarization states, the matrix D²NNs are proposed to process sophisticated inference tasks by encoding polarization-sensitive Jones matrix into the all-optical polarization multiplexing networks (38). In addition to wavelength and polarization, rotation angle is another degree of freedom that can be used to design angle-dependent D²NN for the processing of multiple tasks (39). However, all of the previous D²NN can only implement the corresponding functionalities in a specific direction, i.e., in the forward or backward direction. How to achieve direction-dependent functions, i.e., versatile functionalities in both forward and backward propagating directions, remains a notable challenge.

Copyright © 2025 The Authors, some rights reserved; exclusive licensee American Association for the Advancement of Science. No claim to original U.S. Government Works. Distributed under a Creative Commons Attribution NonCommercial License 4.0 (CC BY-NC).

¹Terahertz Technology Innovation Research Institute, and Shanghai Key Lab of Modern Optical System, University of Shanghai for Science and Technology, No. 516 JunGong Road, Shanghai, 200093, China. ²Shanghai Institute of Intelligent Science and Technology, Tongji University, Shanghai, 200092 China. ³Institute of Photonics and Quantum Sciences, School of Engineering and Physical Sciences, Heriot-Watt University, Edinburgh, EH14 4AS, UK.

*Corresponding author. Email: xzfzang@usst.edu.cn (X.Z.); ymzhu@usst.edu.cn (Y.Z.); x.chen@hw.ac.uk (X.C.)

Unlike 3D printing–based diffractive surfaces with only the phase or amplitude modulation functions, metasurfaces can also manipulate the polarization of EM waves, providing a unique degree of freedom to mimic D^2NN . In particular, the spin-decoupled metasurfaces enable the extraordinary ability to independently manipulate two orthogonal helical components (of EM waves), and thus, a spin-dependent light beam propagating from the forward and backward directions will experience different wavefront modulations, providing a robust approach to achieving directional functionalities.

Here, we propose a distinct approach to designing a directional-diffractive deep neural network ($D-D^2NN$) that showcases the distinct functionalities in the forward and backward directions, opening a degree of freedom to integrate more functions into the D^2NN . Our designed $D-D^2NN$ consists of three layers spin-decoupled metasurfaces, which can independently control the phase functions in opposite propagation directions. This approach provides a flexible platform to mimic direction-dependent D^2NN , leading to a high-capacity directional processor. An image classifier that can identify the handwritten digits and fashion products in the two opposite channels is experimentally demonstrated using the designed $D-D^2NN$. By controlling the distances between the three layers spin-decoupled metasurfaces, a calculation-like processor with addition-, subtraction-, multiplication-, and division-like functions in the four directional-dependent channels are achieved. We further experimentally demonstrate a confidential processor that can transform each input digit into different digits, letters, and images in the direction-dependent channels, leading to the high-capacity information encryption by switching the input information. The approach in designing $D-D^2NN$ with independent functionalities in opposite propagation directions opens a previously unknown dimension to function integration, which will enable applications in data processing and information encryption that require high speed and high capacity.

RESULTS

Figure 1 shows the schematic of three layers spin-decoupled metasurfaces with different interlayer distances to mimic $D-D^2NN$ with high-capacity information processing capability in opposite propagation directions. The input comprises a plethora of ciphertexts “2, 7, 8, ...” propagating from the forward/backward direction, which are processed by the three hidden layers to decode distinct information (from the directional channels). Upon the illumination of left circularly polarized (LCP) terahertz (THz) waves from the forward direction, the decoded information “S, E, C, ...” is achieved for the interlayer distance of d_1 , while another decoded messages “R, E, T, ...” are obtained for the incidence of LCP THz waves from the backward direction. Furthermore, the decoded images “sun, cloud, thunder ...”/“half-moon, full-moon, stars, ...” are observed in the opposite channels for the interlayer distance of d_2 . The target/true information can be revealed by synthesizing the decoded information across the four direction-dependent channels. Since the true messages are divided into the four directional channels, the partial information interception cannot restore the true information, leading to the information encryption facilitated by the $D-D^2NN$ with security-sharing function (or distinct functions) due to the high-capacity directional information processing in the versatily directional channels.

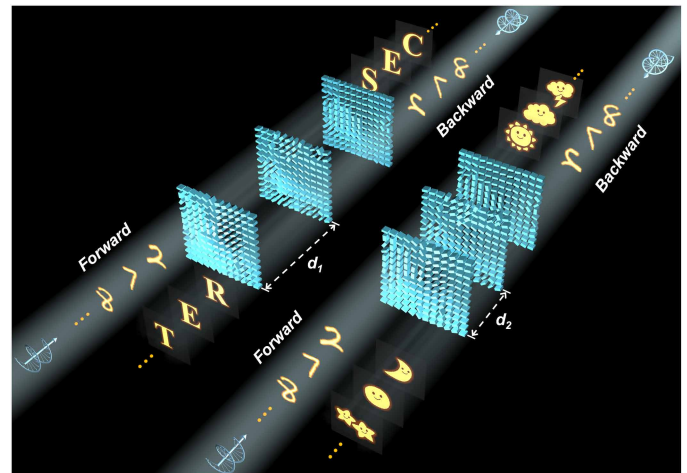


Fig. 1. Schematic of directional D^2NN with high-capacity information processing functionalities. When the distance between two neighboring metasurfaces is d_1 , the decoded target information S, E, C, .../R, E, T, ... in the forward/backward direction for the same input ciphertexts 2, 7, 8, ... When the distance is switched into d_2 , the decoded target information sun, cloud, thunder .../half-moon, full-moon, stars, ... in the forward/backward direction for the same input ciphertexts 2, 7, 8, ...

$D-D^2NN$ design

To further demonstrate our proposed $D-D^2NN$ that is different from the traditional D^2NN , two schematics are illustrated in Fig. 2A. The conventional D^2NN is limited to achieve a single function in the forward direction, while $D-D^2NN$ enables the capabilities in simultaneously controlling phases in both forward and backward propagating directions, allowing for distinct functions in the two opposite channels. The operating principle of our design is shown in Fig. 2B. For the incidence of LCP THz waves from the forward direction, the diffractive field after a mask will be firstly modulated by layer 1 with phase1_L (the phase in the LCP channel) and then modulated by phase2_R [the phase in the right circularly polarized (RCP) channel of layer 2] and phase3_L (the phase in the LCP channel of layer 3) from layers 2 and 3, respectively. In contrast, when the LCP THz waves are illuminated from the backward direction, the sequential order of the phase modulations (for the diffractive field after a mask) is phase3_R, phase2_L, and phase1_R, respectively. Since each hidden layer consists of spin-decoupled metasurface, the phases of phase1_L/phase2_R/phase3_L and phase1_R/phase2_L/phase3_R in layer 1/2/3 (see the phase profiles in Fig. 2D) can be independently controlled in two orthogonal polarization channels. Therefore, phase modulations in the opposite propagating channels are the two uncorrelated phases that can be independently manipulated to generate different functions. In experiment, we mimic the backward incidence by horizontally rotating each metasurface with 180° along the y axis and spatially exchanging the layer 1 and layer 3 while maintaining the incidence of LCP THz waves from the forward direction.

To realize directional-dependent functionalities, the $D-D^2NN$ are trained on the basis of optical diffraction theory. Each hidden layer is implemented by a spin-decoupled metasurface encoded with the trained phases of phase $_i$ _L and phase $_i$ _R ($i = 1, 2$, or 3), which are obtained by deep learning algorithms (i.e., error back propagation algorithm and random gradient descent optimization method). Each meta-atom in a metasurface functions as an optical

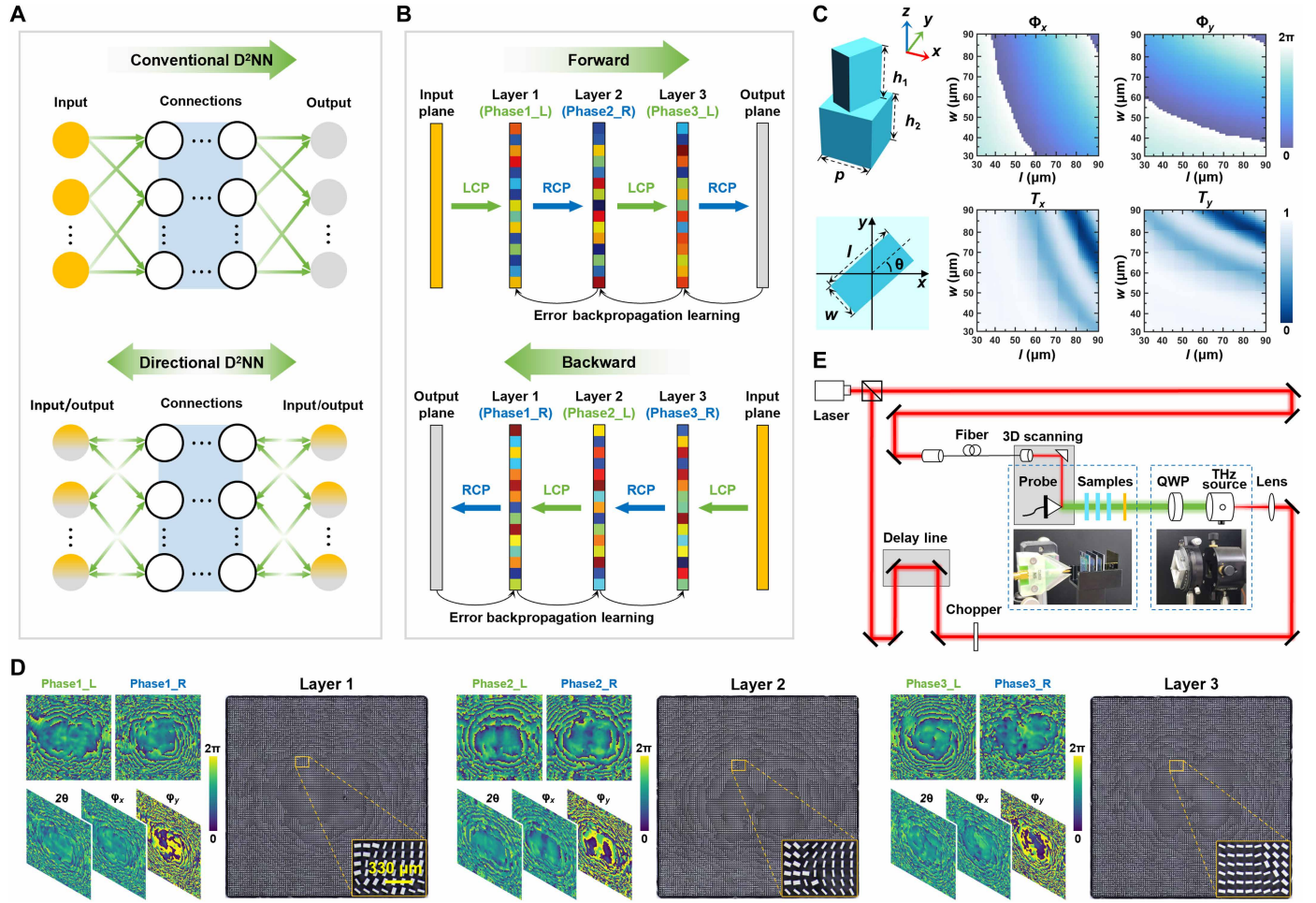


Fig. 2. Mechanism, design, and experimental setup. (A) Schematics of the comparison between conventional D²NN and our proposed D-D²NN. (B) Operating principle of the D-D²NN in both forward and backward propagating directions. (C) Schematics of a meta-atom in a metasurface and the simulated phase shifts (Φ_x and Φ_y) and transmission coefficients (T_x and T_y) under the illumination of x- and y-polarized THz waves. (D) Calculated phases and fabricated samples of spin-decoupled metasurfaces for realizing the calculation-like processor. (E) Experimental setup for demonstrating D-D²NN with versatilely directional functions, including a quarter-wave plate (QWP).

neuron, which interacts with other neurons in preceding and subsequent layers based on diffraction. According to Rayleigh-Sommerfeld diffraction theory, the connection between the diffractive field $E(\mathbf{r}^l)$ from the l^{th} layer and $E(\mathbf{r}^{l+1})$ from the $(l+1)^{\text{th}}$ layer can be expressed as

$$E(\mathbf{r}^{l+1}) = \iint_S E(\mathbf{r}^l) \cdot e^{j\Phi_F^l} \cdot h(\mathbf{r}^{l+1} - \mathbf{r}^l) dx dy \quad (1)$$

where Φ_F^l is the spin-decoupled phase in the forward direction of the l^{th} hidden layer. $h(\mathbf{r}^{l+1} - \mathbf{r}^l)$ is the impulse response that can be defined as

$$h(\mathbf{r}^{l+1} - \mathbf{r}^l) = \frac{z^{l+1} - z^l}{R^2} \left(\frac{1}{2\pi R} - \frac{1}{j\lambda} \right) \exp(j\frac{2\pi R}{\lambda}) \quad (2)$$

where λ is the working wavelength and $R = \sqrt{(x^{l+1} - x^l)^2 + (y^{l+1} - y^l)^2 + (z^{l+1} - z^l)^2}$. j is the imaginary number

of $\sqrt{-1}$. In addition, loss functions and a stochastic gradient descent approach are used to construct the forward/backward propagation models of D²NN. The details about the model training, derivation, and integration of D-D²NN are supplied in section S1. The potential methods for introducing nonlinear operation into D-D²NN are discussed in section S2.

To achieve the versatile functionalities in the opposite channels, we design spin-decoupled metasurfaces consisting of abundant anisotropic meta-atoms with different lengths (l), widths (w), and in-plane orientations (θ), as shown in Fig. 2C. The height of rod (h_1) and substrate (h_2) of each meta-atom is fixed (i.e., 500 μm), while the period (p) of each unit cell is 110 μm . The transmission coefficients and phase shifts upon the x- and y-polarized THz waves (at 0.7 THz) are shown in Fig. 2C. For the spin-decoupled metasurfaces, each meta-atom is optimized and selected to meet the conditions: $|\Phi_x - \Phi_y| \approx \pi$ and $T_x \approx T_y \geq 70\%$, serving as a quasi-half-waveplate. The spin-decoupled phases with detailed Pancharatnam-Berry (2θ) and propagation phases (Φ_x and Φ_y) for the hidden layers are shown in Fig. 2D. The directional

functionalities of our constructed D-D²NN are experimentally demonstrated by a near-field scanning THz microscopy, as shown in Fig. 2E. A femtosecond laser beam is divided into two parts, in which one part impinges onto a photoconductive antenna to generate THz radiation, while the other part is guided to a THz tip to detect field intensity distributions after the samples. Detailed information about the experimental setup is provided in Materials and Methods.

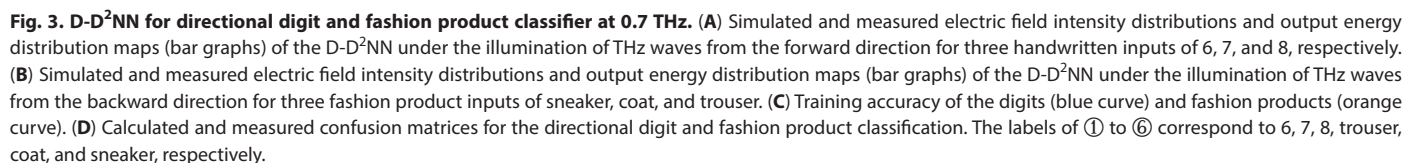
Image classifier in two channels

As a guided study, the D-D²NN with directional functionalities in two opposite channels are numerically simulated and experimentally demonstrated in Fig. 3. To realize the directional digit and fashion product classification, two classical datasets from Modified National Institute of Standards and Technology (MNIST) and Fashion-MNIST are used for machine learning. In the forward direction, digits “6,” “7,” and “8” are selected to verify the digit recognition, while the fashion product classification in the backward direction is certified by using the “sneaker,” “coat,” and “trouser,” respectively. All-dielectric three-layered spin-decoupled metasurfaces are designed as the hidden layers to directionally recognize digits and fashion products. The working frequency of metasurfaces is 0.7 THz, and each metasurface consists of 120 by 120 meta-atoms, i.e., 14,400 neurons for each hidden layer. The distances between the input plane, hidden layers, and output plane are $d_1 = d_4 = 5$ mm and $d_2 = d_3 = 10$ mm. After training the digits 6, 7, and 8 and extracting the network output phase profiles, the forward digit recognition can be achieved by encoding the trained phase profiles into the LCP, RCP, and LCP polarization channels of layers 1, 2, and 3. Meanwhile, the fashion product classification can be integrated in the backward direction (of the D-D²NN) by encoding the corresponding phase profiles into RCP, LCP, and RCP polarization channels of layers 1, 2, and 3. To simultaneously distinguish and identify digits and fashion products, the physical plane of our designed network output contains six discrete detection regions. The top three discrete detection regions are designed for the recognition of digits, while the bottom three discrete detection regions are used for the identification of fashion products. As shown in Fig. 3A for the incidence of LCP THz waves from the forward direction, the calculated electric field intensity distributions in the output plane are located at the top left corner for the input of handwritten digit 6. The calculated intensity distribution map shown in Fig. 3A demonstrates that our designed D²NN can rightly identify the handwritten digit 6. For the input of digits 7 and 8, the forward channel of our proposed D-D²NN enables the function in focusing the incident LCP THz waves into the top middle and top right corners in the output plane. The calculated intensity distribution maps also matched with the corresponding electric field intensity distributions in the output plane. In the experiment, for the input of fabricated samples with digits 6, 7, and 8, the measured electric field intensity distributions in the output plane are located at top left, top middle, and top right corners, which demonstrate that the fabricated three-layered spin-decoupled metasurfaces can recognize handwritten digits in the forward channel. The measured intensity distribution maps in Fig. 3A are agreed with our predesigned results. In contrast, when an LCP THz beam propagates from the backward direction, another different function in recognizing fashion products is achieved, as shown in Fig. 3B. For the input of fashion products of sneaker, coat, and trouser, the calculated electric field intensity distributions are focused in the

bottom left, bottom middle, and bottom right corners. The measured electric field intensity distributions shown in Fig. 3B agree well with the simulated results, demonstrating the classification of fashion products in the backward direction. The calculated and measured intensity distribution maps in Fig. 3B are agreed with our predesigned results. In the digit and fashion product identification, each category (i.e., digits or fashion products) is iteratively trained for 100 periods, as shown in Fig. 3C. The training accuracy for digit/fashion products has reached 96.2/98.5%. In addition, 2932 handwritten digit (3000 fashion products) images are used as the test datasets, while 15 handwritten digit (15 fashion products) samples are fabricated as the experimental validation datasets. As shown in Fig. 3D, the confusion matrices are constructed to illustrate the identified and misidentified instances in simulation and experiment. The test accuracy in simulation is 96.2/98.5% in the forward/backward direction, while it is 93.3/93.3% in experiment, as shown in Fig. 3D. The experiment results of output electric field intensity distribution for five different appearances per category as the input are presented in section S3. To further demonstrate the designed D-D²NN enabling the function in recognizing digits (rather than fashion products) in the forward direction and in identifying fashion products (instead of digits) in the backward direction, the simulated electric field intensity distributions for the input of fashion products/digits in the forward/backward direction are given and discussed in section S4. This proposed approach can identify more numbers of digits and fashion products (i.e., 10 digits and 10 fashion products) in the two opposite channels, which is numerically demonstrated in section S5. In addition to image classification in opposite directions, this proposed D-D²NN enables the hybrid functionalities in image classification and imaging in the forward and backward directions, respectively. The simulated results are provided in section S6.

Calculation-like processor in four channels

Such a D-D²NN approach cannot only has one specific function in each directional channel but also enables the capability of multiplexing multiple functions in the forward and backward channels by altering the interlayer distances between the input plane, hidden layers, and output plane, as shown in Fig. 4. To realize such a D-D²NN with multiple functions in each directional channel, the joint training that combine the different functions (i.e., each function is relative to the specific interlayer distances) together, is implemented to extract the network output phase profiles, and then, the D-D²NN with directional multifunctions are constructed. As a proof-of-concept demonstration, a calculation-like processor with four distinct functions, i.e., addition-, subtraction-, multiplication-, and division-like functions, in four directional channels is achieved. As shown in Fig. 4A for the incidence of LCP THz waves from the forward direction and the input of “62,” the simulated electric field intensity distributions in the detection plane are presented as a digit 8 for the interlayer distances of $d_{11} = d_{14} = 5$ mm and $d_{12} = d_{13} = 10$ mm, leading to an addition-like function in our designed D-D²NN. In contrast, when the LCP THz waves propagate from backward with input of 62, the subtraction-like function is numerically demonstrated by a digit of “4” shown in the output plane. When the interlayer distances are altered to $d_{11} = d_{14} = 10$ mm and $d_{12} = d_{13} = 5$ mm, the simulated electric field intensity distributions in the detection planes are shown as digits of “12” and “3” for the forward and backward incidence, demonstrating the multiplication- and division-like



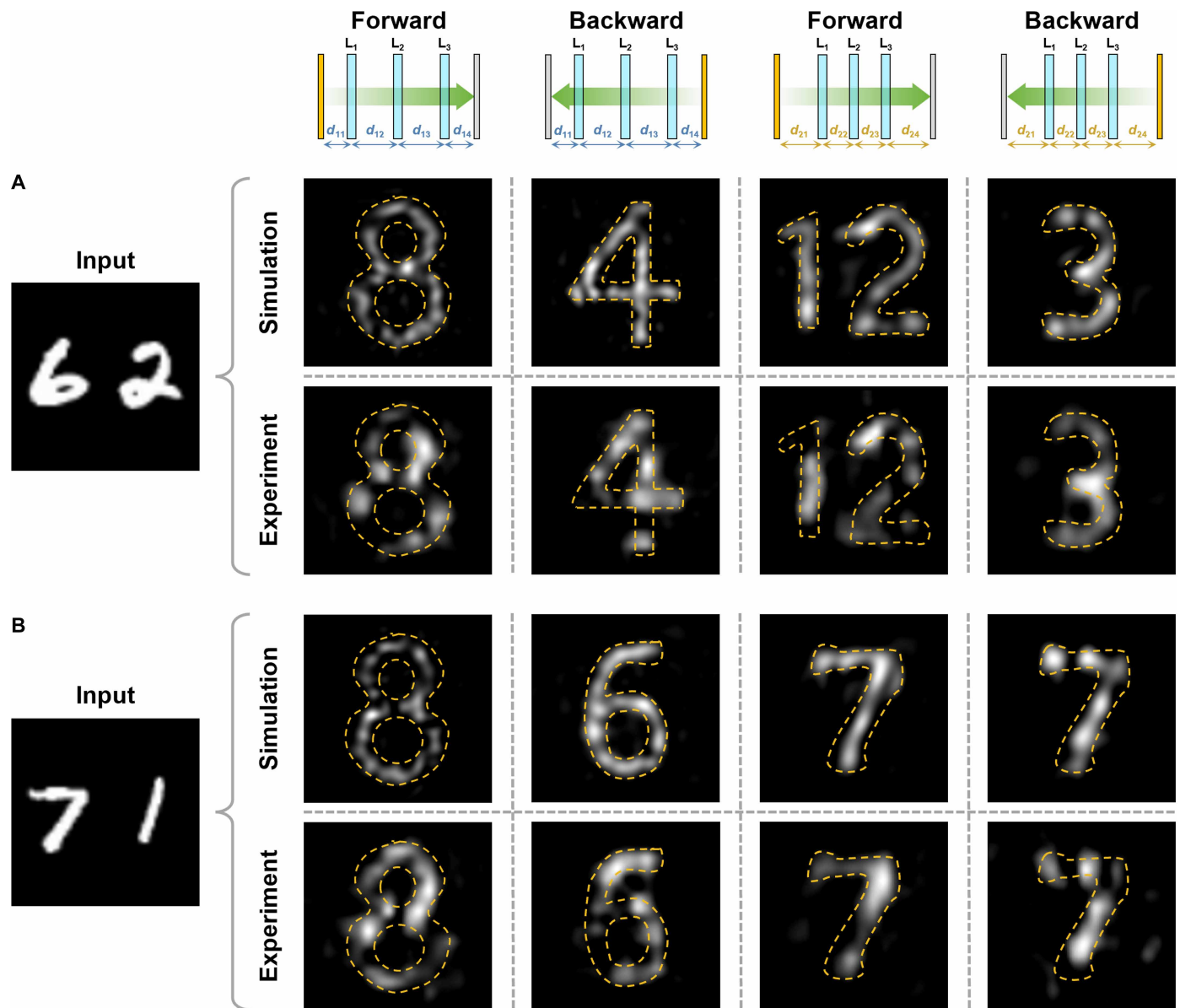


Fig. 4. D-D²NN for a calculation-like processor with addition-, subtraction-, multiplication-, and division-like functions. (A) When the LCP THz waves incident from the forward/backward direction with the input digit of 62, the addition-/subtraction-like function is obtained with the interlayer distances of $d_{11} = d_{14} = 5$ mm and $d_{12} = d_{13} = 10$ mm, while the multiplication-/division-like function is achieved in the forward/backward channel when the interlayer distances are $d_{21} = d_{24} = 10$ mm and $d_{22} = d_{23} = 5$ mm. (B) Numerical and experimental demonstration of the calculation-like processor with addition-, subtraction-, multiplication-, and division-like functions with the input digit of 71.

functions, respectively. In experiment, the addition-, subtraction-, multiplication-, and division-like functions are also implemented with the measured digits of 8, 4, 12, and 3 in the detection planes, when the LCP THz waves incident from the four directional channels. The measured results agree well with the numerical simulations, except for a slightly lower homogeneity in the measured digits which can be attributed to experimental errors. To demonstrate the versatile characteristic of our designed D-D²NN, the addition-, subtraction-, multiplication-, and division-like functions can be also verified by another input digit, as shown in Fig. 4B. For the incidence of LCP THz waves from the forward/backward direction, the

simulated and measured diffractive field in the detection planes are shown as a digit of 8 (addition)/6 (subtraction) for the input of “71” and interlayer distances of $d_{11} = d_{14} = 5$ mm and $d_{12} = d_{13} = 10$ mm. In addition, the digits of 7 (multiplication) and 7 (division) are numerically and experimentally observed in the detection planes (for the forward and backward incidence with the input of 71), when the interlayer distances are changed into $d_{11} = d_{14} = 10$ mm and $d_{12} = d_{13} = 5$ mm. Detailed information for the four directional functions with distinct input digits of 62 and 71 is given in section S7. Although our proposed calculation-like processor can mimic addition-, subtraction-, multiplication-, and division-like functions, it is not a

true calculator, because it can only handle the finite inputs (e.g., the 10 categories of digit groups to 40 other images in section S8) optimized by the neural network. The calculation-like processor demonstrated in this work shows that our proposed D-D²NN enables different functionalities in the four direction- and distance-dependent channels.

High-capacity information encryption processor

The D-D²NN with directional functionalities provide a multichannel platform that can divide a secret/message into four channels, enabling applications in information encryption. For instance, a target message consisting of multiple digits and/or letters can be divided into several parts, in which each part of the message is encoded in a directional channel. Therefore, the information interception from one channel or a part of channels (rather than the whole channels) cannot leak the true information, due to the security-sharing function of our designed D-D²NN. Therefore, four channels of security-sharing enable the capability in improving secrecy performance. Unlike the traditional metasurface-based platform with specific illumination patterns (e.g., Gaussian beams and transverse electric/transverse magnetic mode beams)

and limited information encryption function (40–42), the D-D²NN can process various inputs (i.e., the predefined ciphertexts with various categories and appearances) through deep learning, enabling the high-capacity functionality in information encryption. To decode the target message, four keys with different directions and interlayer distances are designed, as shown in Fig. 5B. For the predefined ciphertexts and four keys, the D-D²NN shown in Fig. 5C can reconstruct the true message. For the input of digit 7 (Fig. 5A), the four keys can decode the information of “M,” “E,” “T,” “A” (Fig. 5D) with our designed D-D²NN. In addition, for the input of digit “2,” the decoded outputs of 4, “H,” 8, and “f” are achieved by using the four keys. Last, the true messages are numerically and experimentally reconstructed as “META” and “4H8f” (Fig. 5E). Notably, one can only obtain a misleading message when the data in four channels are not leaked simultaneously. This processor can handle various appearances of inputs of 7 and 2 that is supplied in section S9. To further verify the high-capacity characteristic in information encryption, calculations for more inputs of ciphertexts and reconstructed messages/images are given in movie S1. The decline in the fidelity of outputs as the input ciphertexts continue to increase is discussed in section S10.

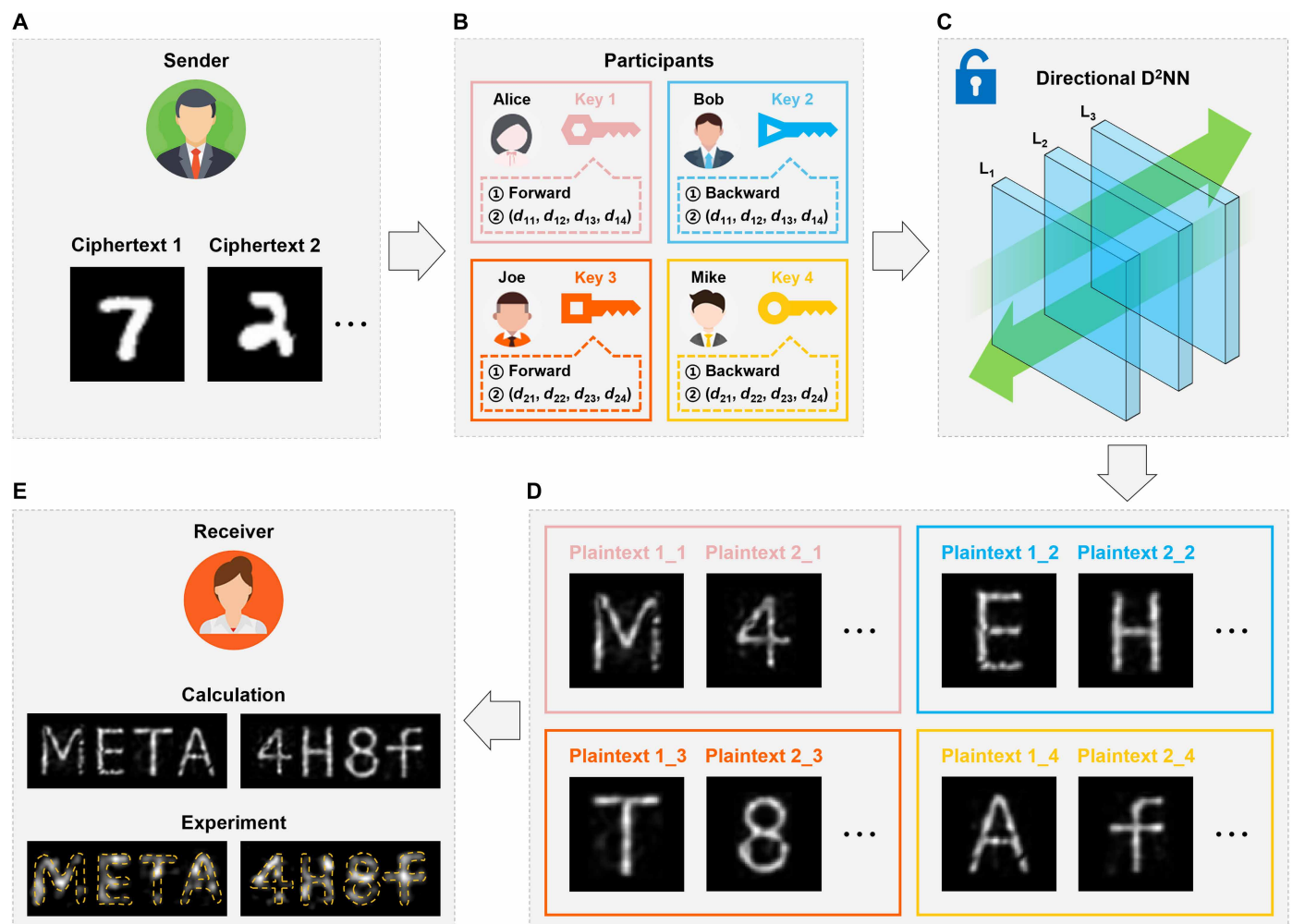


Fig. 5. D-D²NN for high-capacity information encryption. (A) Input of D-D²NN consisting of a plethora of predefined ciphertexts. (B) Keys for decoding the message in the four directional channels. (C) Schematic of D-D²NN. (D) Decoded information in the four directional channels. (E) Decoded plaintext messages.

DISCUSSION

In summary, we propose a spin-decoupled metasurface approach to mimicking D^2NN s that can simultaneously process multiple tasks in both forward and backward propagating directions. The direction-dependent versatile functions of the classification of handwritten digits and fashion products in the opposite directions are experimentally demonstrated because of the independent control of the spin-dependent phases in the forward and backward channels. Multiple functionalities are achieved for each directional channel through the joint training between direction and interlayer distances, leading to a calculation-like processor with finite addition-, subtraction-, multiplication-, and division-like functions in the four directional channels. By dividing the target message into the directional channels, the all-optical information encryption is demonstrated in our proposed $D-D^2NN$, as the leakage of information in a single channel does not disclose the true message. Compared to previous metasurface devices with limited input capacity for information encryption, this $D-D^2NN$ can be trained to handle a variety of inputs (ciphertexts), enabling high-capacity information encryption. Although the proposed $D-D^2NN$ is based on linear optical transformations, it introduces propagation direction in the design (a degree of freedom), offering valuable insights into the current D^2NN . We expect that its capabilities can be further enhanced through the integration of nonlinearity. Despite the uniqueness and potential applications of this technique, the current proof-of-concept demonstration in the THz range is time consuming due to the fabrication of gold masks and the point-by-point scanning of the electric field intensity distributions using a THz tip. However, the proposed $D-D^2NN$ can be extended to both infrared and visible ranges. These challenges can be solved using commercial spatial light modulators to directly generate input images and charge-coupled device cameras to record real-time electric field intensity distributions. Driven by system integration and intelligent D^2NN s, there is an increasing interest in integrating multiple functions into a D^2NN . Propagation direction is a fundamental property of EM waves, which provides a previously unknown avenue to multiplex D^2NN with rich functions in the opposite channels. The robust approach for designing $D-D^2NN$ with distinct functions in two opposite directions will have promising applications including parallel computing, information security, and high-capacity information processing.

MATERIALS AND METHODS

Training methods

The $D-D^2NN$ is implemented using PyTorch framework (v1.10.2) on Windows 11 operating system (Microsoft) with an Intel(R) Core(TM) i9-13900H central processing unit at 2.6 GHz, a GeForce RTX 4060 graphics processing unit (NVIDIA), and a 16-GB random-access memory. To update the phase of each layer in the $D-D^2NN$, we use the mean squared error loss function and the Adam optimizer, with a training batch size of 8 and a learning rate of 0.001. The $D-D^2NN$ for directional classification shown in Fig. 3 is trained for 100 epochs using the MNIST dataset for the forward channel and 100 epochs using the Fashion-MNIST dataset for the backward channel. For the $D-D^2NN$ as a calculation-like processor (or a high-capacity information encryption platform) shown in Fig. 4 (or Fig. 5), the MNIST dataset and the ground truth (i.e., target images) with the calculation results (or the encryption

plaintexts) are applied for 300 training epochs on the forward and backward channels.

Sample fabrication

The 1000- μm -thick intrinsic silicon wafers (orient: $\langle 100 \rangle$, R : $>10,000$ ohm-cm, polish: double-side polish) from HF-Kejing Company are prepared for the fabrication of metasurfaces. The first step is cleaning the silicon wafers in an ultrasonic bath and then spin-coated the AZP4620 photoresist layer (thickness: 7 to 8 μm) onto the wafers at 6000 rpm. The photoresist film is then baked on a hotplate at 100°C for about 1 min. The resist film is exposed using a mask aligner (SF-100, Intelligent Micro Patterning). After that, the resist film with micropillars is baked again at 100°C for 2 min and etched using the deep reactive ion etching (Bosch) process with SF_6 and C_4F_8 for about 95 min. Last, the meta-atoms of metasurfaces with distinct shapes are obtained after removing the photoresist using acetone. For the gold masks (i.e., the input of the $D-D^2NN$), the photoresist is spin-coated onto one side of the silica film and then exposed. Last, the gold mask is formed after metal coating and ultrasonic stripping.

Experimental setup

A near-field scanning terahertz time domain spectrum microscopy system is constructed to scan the output electric field intensity distributions of our proposed $D-D^2NN$, as shown in Fig. 2E. A femto-second laser with a central wavelength of 780 nm is split into two paths. One path of laser beam is directly guided into a photoconductive antenna emitter to generate THz waves that impinge onto the $D-D^2NN$ samples. The other path of laser beam is coupled into a single-mode fiber and then transmit to the THz probe (i.e., a THz tip) that is mounted on a 3D scanning stage. The samples are fixed on a holder with a series of slots. The THz probe scans after the samples to probe the electric field intensity distributions on the output plane of the $D-D^2NN$.

Supplementary Materials

The PDF file includes:

Supplementary Text
Sections S1 to S10
Figs. S1 to S8
Table S1
Legend for movie S1
References

Other Supplementary Material for this manuscript includes the following:

Movie S1

REFERENCES AND NOTES

1. H. J. Caulfield, S. Dolev, Why future supercomputing requires optics. *Nat. Photonics* **4**, 261–263 (2010).
2. G. Wetzstein, A. Ozcan, S. Gigan, S. Fan, D. Englund, M. Soljačić, C. Denz, D. A. B. Miller, D. Psaltis, Inference in artificial intelligence with deep optics and photonics. *Nature* **588**, 39–47 (2020).
3. L. Larger, A. Baylón-Fuentes, R. Martinenghi, V. S. Udaltsov, Y. K. Chembo, M. Jacquot, High-speed photonic reservoir computing using a time-delay-based architecture: Million words per second classification. *Phys. Rev. X* **7**, 011015 (2017).
4. J. Feldmann, N. Youngblood, C. D. Wright, H. Bhaskaran, W. H. P. Pernice, All-optical spiking neurosynaptic networks with self-learning capabilities. *Nature* **569**, 208–214 (2019).
5. Y. Shen, N. C. Harris, S. Skirlo, M. Prabhu, T. Baehr-Jones, M. Hochberg, X. Sun, S. Zhao, H. Laroche, D. Englund, M. Soljačić, Deep learning with coherent nanophotonic circuits. *Nat. Photonics* **11**, 441–446 (2017).

6. H. H. Zhu, J. Zou, H. Zhang, Y. Z. Shi, S. B. Luo, N. Wang, H. Cai, L. X. Wan, B. Wang, X. D. Jiang, J. Thompson, X. S. Luo, X. H. Zhou, L. M. Xiao, W. Huang, L. Patrick, M. Gu, L. C. Kwek, A. Q. Liu, Space-efficient optical computing with an integrated chip diffractive neural network. *Nat. Commun.* **13**, 1044 (2022).
7. X. Lin, Y. Rivenson, N. T. Yardimci, M. Veli, Y. Luo, M. Jarrahi, A. Ozcan, All-optical machine learning using diffractive deep neural networks. *Science* **361**, 1004–1008 (2018).
8. S. Gao, H. Chen, Y. Wang, Z. Duan, H. Zhang, Z. Sun, Y. Shen, X. Lin, Super-resolution diffractive neural network for all-optical direction of arrival estimation beyond diffraction limits. *Light Sci. Appl.* **13**, 161 (2024).
9. M. K. Chen, X. Liu, Y. Sun, D. P. Tsai, Artificial intelligence in meta-optics. *Chem. Rev.* **122**, 15356–15413 (2022).
10. D. Mengü, Y. Luo, Y. Rivenson, A. Ozcan, Analysis of diffractive optical neural networks and their integration with electronic neural networks. *IEEE J. Sel. Top. Quantum Electron.* **26**, 1–14 (2020).
11. M. S. Rahman, J. Li, D. Mengü, Y. Rivenson, A. Ozcan, Ensemble learning of diffractive optical networks. *Light Sci. Appl.* **10**, 14 (2021).
12. J. Li, D. Mengü, Y. Luo, Y. Rivenson, A. Ozcan, Class-specific differential detection in diffractive optical neural networks improves inference accuracy. *Adv. Photonics* **1**, 046001 (2019).
13. Z. Zhao, Y. Wang, C. Guan, K. Zhang, Q. Wu, H. Li, J. Liu, S. N. Burokur, X. Ding, Deep learning-enabled compact optical trigonometric operator with metasurface. *Photonix* **3**, 15 (2022).
14. Y. Luo, Y. Zhao, J. Li, E. Çetintas, Y. Rivenson, M. Jarrahi, A. Ozcan, Computational imaging without a computer: Seeing through random diffusers at the speed of light. *eLight* **2**, 4 (2022).
15. J. Li, B. Bai, Y. Luo, A. Ozcan, Massively parallel universal linear transformations using a wavelength-multiplexed diffractive optical network. *Adv. Photonics* **5**, 016003 (2023).
16. J. Li, T. Gan, Y. Zhao, B. Bai, C.-Y. Shen, S. Sun, M. Jarrahi, A. Ozcan, Unidirectional imaging using deep learning-designed materials. *Sci. Adv.* **9**, eadg1505 (2023).
17. B. Bai, X. Yang, T. Gan, J. Li, D. Mengü, M. Jarrahi, A. Ozcan, Pyramid diffractive optical networks for unidirectional image magnification and demagnification. *Light Sci. Appl.* **13**, 178 (2024).
18. J. Li, Y. Li, T. Gan, C.-Y. Shen, M. Jarrahi, A. Ozcan, All-optical complex field imaging using diffractive processors. *Light Sci. Appl.* **13**, 120 (2024).
19. D. Mengü, A. Tabassum, M. Jarrahi, A. Ozcan, Snapshot multispectral imaging using a diffractive optical network. *Light Sci. Appl.* **12**, 86 (2023).
20. N. Yu, P. Genevet, M. A. Kats, F. Aieta, J.-P. Tetienne, F. Capasso, Z. Gaburro, Light propagation with phase discontinuities: Generalized laws of reflection and refraction. *Science* **334**, 333–337 (2011).
21. L. Huang, X. Chen, H. Mühlenbernd, G. Li, B. Bai, Q. Tan, G. Jin, T. Zentgraf, S. Zhang, Dispersionless phase discontinuities for controlling light propagation. *Nano Lett.* **12**, 5750–5755 (2012).
22. M. Khorasaninejad, W. Zhu, K. B. Crozier, Efficient polarization beam splitter pixels based on a dielectric metasurface. *Optica* **2**, 376–382 (2015).
23. Y. Deng, C. Wu, C. Meng, S. I. Bozhevolnyi, F. Ding, Functional metasurface quarter-wave plates for simultaneous polarization conversion and beam steering. *ACS Nano* **15**, 18532–18540 (2021).
24. X. Yin, Z. Ye, J. Rho, Y. Wang, X. Zhang, Photonic spin Hall effect at metasurfaces. *Science* **339**, 1405–1407 (2013).
25. L. Li, Z. Liu, X. Ren, S. Wang, V.-C. Su, M.-K. Chen, C. H. Chu, H. Y. Kuo, B. Liu, W. Zang, G. Guo, L. Zhang, Z. Wang, S. Zhu, D. P. Tsai, Metalens-array-based high-dimensional and multiphoton quantum source. *Science* **368**, 1487–1490 (2020).
26. T. Santiago-Cruz, S. D. Gennaro, O. Mitrofanov, S. Addamane, J. Reno, I. Brener, M. V. Chekhova, Resonant metasurfaces for generating complex quantum states. *Science* **377**, 991–995 (2022).
27. L. Huang, X. Chen, H. Mühlenbernd, H. Zhang, S. Chen, B. Bai, Q. Tan, G. Jin, K.-W. Cheah, C.-W. Qiu, J. Li, T. Zentgraf, S. Zhang, Three-dimensional optical holography using a plasmonic metasurface. *Nat. Commun.* **4**, 2808 (2013).
28. D. Wen, F. Yue, G. Li, G. Zheng, K. Chan, S. Chen, M. Chen, K. F. Li, P. W. H. Wong, K. W. Cheah, E. Y. B. Pun, S. Zhang, X. Chen, Helicity multiplexed broadband metasurface holograms. *Nat. Commun.* **6**, 8241 (2015).
29. G. Zheng, H. Mühlenbernd, M. Kenney, G. Li, T. Zentgraf, S. Zhang, Metasurface holograms reaching 80% efficiency. *Nat. Nanotechnol.* **10**, 308–312 (2015).
30. N. K. Grady, J. E. Heyes, D. R. Chowdhury, Y. Zeng, M. T. Reiten, A. K. Azad, A. J. Taylor, D. A. R. Dalvit, H.-T. Chen, Terahertz metamaterials for linear polarization conversion and anomalous refraction. *Science* **340**, 1304–1307 (2013).
31. X. Zang, F. Dong, F. Yue, C. Zhang, L. Xu, Z. Song, M. Chen, P.-Y. Chen, G. S. Buller, Y. Zhu, S. Zhuang, W. Chu, S. Zhang, X. Chen, Polarization encoded color image embedded in a dielectric metasurface. *Adv. Mater.* **30**, e1707499 (2018).
32. X. Chen, L. Huang, H. Mühlenbernd, G. Li, B. Bai, Q. Tan, G. Jin, C.-W. Qiu, S. Zhang, T. Zentgraf, Dual-polarity plasmonic metalens for visible light. *Nat. Commun.* **3**, 1198 (2012).
33. M. Khorasaninejad, W. T. Chen, R. C. Devlin, J. Oh, A. Y. Zhu, F. Capasso, Metalenses at visible wavelengths: Diffraction-limited focusing and subwavelength resolution imaging. *Science* **352**, 1190–1194 (2016).
34. W. T. Chen, A. Y. Zhu, V. Sanjeev, M. Khorasaninejad, Z. Shi, E. Lee, F. Capasso, A broadband achromatic metalens for focusing and imaging in the visible. *Nat. Nanotechnol.* **13**, 220–226 (2018).
35. H. Chi, X. Zang, T. Zhang, G. Wang, Z. Fan, Y. Zhu, X. Chen, S. Zhuang, Metasurface enabled multi-target and multi-wavelength diffraction neural networks. *Laser Photonics Rev.* **18**, 2401178 (2024).
36. Y. Li, J. Li, Y. Zhao, T. Gan, J. Hu, M. Jarrahi, A. Ozcan, Universal polarization transformations: Spatial programming of polarization scattering matrices using a deep learning-designed diffractive polarization transformer. *Adv. Mater.* **35**, e2303395 (2023).
37. X. Luo, Y. Hu, X. Ou, X. Li, J. Lai, N. Liu, X. Cheng, A. Pan, H. Duan, Metasurface-enabled on-chip multiplexed diffractive neural networks in the visible. *Light Sci. Appl.* **11**, 158 (2022).
38. Y. Wang, A. Yu, Y. Cheng, J. Qi, Matrix diffractive deep neural networks merging polarization into meta-devices. *Laser Photonics Rev.* **18**, 2300903 (2024).
39. G. Ma, X. Yang, B. Bai, J. Li, Y. Li, T. Gan, C.-Y. Shen, Y. Zhang, Y. Li, Ç. Işıl, M. Jarrahi, A. Ozcan, Multiplexed all-optical permutation operations using a reconfigurable diffractive optical network. *Laser Photonics Rev.* **18**, 2400238 (2024).
40. Y. Chen, X. Yang, J. Gao, 3D Janus plasmonic helical nanoapertures for polarization-encrypted data storage. *Light Sci. Appl.* **8**, 45 (2019).
41. M. Liu, P. Huo, W. Zhu, C. Zhang, S. Zhang, M. Song, S. Zhang, Q. Zhou, L. Chen, H. J. Lezec, A. Agrawal, Y. Lu, T. Xu, Broadband generation of perfect Poincaré beams via dielectric spin-multiplexed metasurface. *Nat. Commun.* **12**, 2230 (2021).
42. P. Georgi, Q. Wei, B. Sain, C. Schlickriede, Y. Wang, L. Huang, T. Zentgraf, Optical secret sharing with cascaded metasurface holography. *Sci. Adv.* **7**, eabf9718 (2021).
43. R. C. Devlin, A. Ambrosio, N. A. Rubin, J. P. B. Mueller, F. Capasso, Arbitrary spin-to-orbital angular momentum conversion of light. *Science* **358**, 896–901 (2017).
44. E. Wolf, E. W. Marchand, Comparison of the Kirchhoff and the Rayleigh-Sommerfeld theories of diffraction at an aperture. *J. Opt. Soc. Am.* **54**, 587–594 (1964).
45. B. Bai, R. Lee, Y. Li, T. Gan, M. Jarrahi, A. Ozcan, Information-hiding cameras: Optical concealment of object information into ordinary images. *Sci. Adv.* **10**, eadn9420 (2024).

Acknowledgments: The data computing platform are provided by the “SciPlus with Universities” project. Thanks to the project sponsor “Shanghai Science and Technology Innovation Resources Center (SSTIR)” and the organizer “Shanghai Science and Technology Development Co. Ltd. (SSTD).” **Funding:** This work was supported by the National Natural Science Foundation of China (62588201 and 61988102), “Shuguang” Program of Shanghai Education Commission (19SG44), Science and Technology Commission of Shanghai Municipality (21S31907400), Shanghai Municipal Science and Technology Commission (22JC1400200), and Leverhulme Trust (RPG-2023-283 and RPG-2021-145). **Author contributions:** Conceptualization: X.Z., G.W., X.C., and Y.Z. Methodology: G.W., X.Z., Z.T., T.Z., Z.G., and S.Z. Investigation: G.W., X.Z., and X.C. Visualization: G.W. Funding acquisition: X.Z., X.C., and Y.Z. Project administration: X.Z., X.C., and Y.Z. Supervision: X.Z. Writing—original draft: X.Z., X.C., and G.W. Writing—review and editing: G.W., X.Z., X.C., and Z.T. **Competing interests:** The authors declare that they have no competing interests. **Data and materials availability:** All data needed to evaluate the conclusions in the paper are present in the paper and/or the Supplementary Materials.

Submitted 23 October 2024
 Accepted 22 October 2025
 Published 21 November 2025
 10.1126/sciadv.adu0904