

Integrated Polarization, Distance, and Rotation for Multi-DoF Diffractive Processor and Information Encryption

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All-optical diffractive deep neural networks (D^2NN s) offer significant advantages in processing speed and power consumption, thereby accelerating the development of optical computing and artificial intelligence (AI). Integrating multiple degrees of freedom (multi-DoF) into D^2NN s is a pivotal role in improving information processing and task-loading capacity, an enormous challenge in current all-optical diffractive computing/processors. Here, a multi-DoF diffractive processor is proposed and experimentally demonstrated that leverages a metasurfaces-based approach to integrate polarization, distance, and rotation channels for versatile inference tasks and information encryption. The approach is validated using three-layer metasurfaces that enable high task-capacity tasks, including single-/dual-digit and single-/dual-fashion-product classification, logic operators, and image transformation. Moreover, by mapping large volumes of input data into multi-DoF channels and encoding the information in Morse code with our D^2NN s framework, a high-security information transmission system is experimentally implemented. The integration of polarization, distance, and rotation channels into an all-optical diffractive processor with multifunctional capabilities paves the way for multifunctional integrated devices and communication.

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DOI: 10.1002/adma.202506222

1. Introduction

Benefitting from light-speed processing, low power consumption, and massively parallel characteristics, there is an increasing interest in optical computing,^[1–5] where photons serve utilized as information carriers. As the cornerstone of optical computing, a variety of all-optical processors with specific functionalities are essential for developing versatile artificial intelligence (AI) systems capable of handling large volumes of data and tasks.^[6–14] Existing all-optical processors can be categorized into two types: integrated photonics-based processors^[6,8,10,11,14] and diffractive optical processors.^[7,9,12,13] Among them, the diffractive optical processors offer unique capabilities by performing computations solely through light propagation and diffraction, without any need for optoelectronic conversion or preprocessing of the input information.^[15–22] By employing deep learning and error-back propagation methods to train D^2NN s on a digital computer, the resulting transmissive layers can be further fabricated to construct a

physical, all-optical diffractive optical processor. D^2NN s leverage the natural propagation and diffraction of light through diffractive surfaces to execute calculations, offering dramatic advantages in optical information processing. This technology has enabled applications in logic operations,^[23,24] image reconstruction,^[17,25] object classification,^[15,26] and quantitative phase imaging.^[27] Despite these achievements, integrating multiple functionalities into D^2NN s remains a crucial challenge for developing compact and fully integrated AI systems.

Recently, multiplexing techniques have emerged as the most effective solution for enhancing function integration in D^2NN s. By exploiting the intrinsic properties of light, such as wavelength and polarization, a plethora of D^2NN s with multiplexed functionalities have been demonstrated.^[28–36] For example, multi-wavelength complex-field imaging, spatially-controlled wavelength demultiplexing,^[28] and multispectral imaging have been achieved by training multiple tasks at different wavelengths.^[29] Moreover, by combining the wavelength-multiplexing techniques with the multi-target classification frameworks, the multi-target diffractive neural networks (DNN s) operating at distinct wavelengths have been designed.^[32] In addition,

polarization degree of freedom (DoF) can be utilized to multiplex different functionalities into D²NNs, enabling polarization-multiplexed parallel computing.^[33–36] For instance, a single-layer diffractive network that embeds two distinct tasks into two orthogonally linearly-polarized (LP) channels has been used to construct metasurface-enabled dual-channel polarization-multiplexed DNNs for the simultaneous classification of digits and fashion products.^[33] Furthermore, by synthesizing trainable polarization modulation neurons into the D²NNs, an enhanced polarization-multiplexed encoding capacity has been realized.^[36] Other recent studies have focused on exploring new DoFs to enhance the function integration of D²NNs, particularly through manipulating the direction of light propagation and the rotation between physical networks. The wave propagation direction is a fundamental property of light and can be integrated into D²NNs with a range of additional functions.^[37,38] For instance, a pyramid-structured DNN has been designed for unidirectional image magnification and demagnification in opposite propagation directions.^[38] Similarly, rotation angle has emerged as another effective parameter to enhance D²NNs integration.^[39,40] By leveraging this spatial DoF, the high-dimensional permutation operations between the input and output field-of-view have been implemented via layer rotations.^[39] Moreover, a physical twisted neural network has been proposed to mimic the optical behavior of meta-disk, thereby expanding the capacity limits of optical holographic storage.^[40]

These remarkable achievements demonstrate the unique capabilities of D²NNs by leveraging various properties of light and spatial dimensions. However, current multiplexing techniques in D²NNs are typically restricted to a single DoF. The design methodology for simultaneously integrating multiple DoFs (*i.e.*, polarization, distance, and rotation) into unified D²NNs to enhance task-loading capacity remains largely unexplored. Furthermore, multi-DoF multiplexed D²NNs enable the creation of versatile and independent channels for information encoding and manipulation, with each channel serving a dedicated function in security-sharing through the assignment of secret keys. By synthesizing or aggregating information across these independent channels, a robust and scalable platform for optical information encryption can be established. Compared to traditional single-DoF multiplexing, the multi-DoF approach introduces additional dimensions for data protection, thereby significantly reducing the risk of information leakage and enhancing overall security.

In this study, we propose and experimentally demonstrate the design of multi-DoF multiplexed D²NNs that integrate polarization, distance, and rotation to perform multiple diffractive computing functionalities and enable high-security information encryption. Our approach leverages a cascaded metasurface platform—characterized by its multifunctional integration and flexible wavefront control—to implement diverse computational tasks.^[41–50] First, we design multi-DoF D²NNs to perform classification tasks, including handwritten digits, fashion product recognition, as well as image transformation. We then extend our design to develop advanced multi-DoF D²NNs to implement multi-task classification and logic operation simultaneously. Moreover, we experimentally demonstrate a high-security information transmission framework by dividing the input information into the multi-DoF channels and then transforming them into the Morse code by our proposed D²NNs, and finally decoding

the Morse code to synthesize the true information. Our multi-DoF multiplexed D²NNs showcase high-capacity capabilities in multidimensional parallel computing and security information transmission, with potential applications in privacy protection, optical storage, and communication networks.

2. Results

2.1. Principle and Methodology

Our multi-DoF multiplexed D²NNs consist of three layers of metasurfaces with controlled interlayer distances and rotation angles between the physical networks (**Figure 1a**). The metallic patterns (*e.g.*, handwritten digits, letters, or fashion products) generate spatially modulated electromagnetic (EM) fields as the input for the system. Each engineered diffractive surface is trained further to harness the phase of these incoming EM fields. By precisely controlling the polarization of the incident EM waves, as well as the distance and rotation of metasurface layers, our multi-DoF multiplexed D²NNs can achieve a wide range of functionalities, including digit/fashion classification and image transformation, as shown in the top portion of **Figure 1a**. Moreover, the multi-DoF multiplexed D²NN framework can be extended to develop a high-security information transmission system, as illustrated in the bottom portion of **Figure 1a**. In this system, the input information is distributed across multiple DoF channels that serve as secret keys and is then processed by the three-layer network. Various Morse code patterns are generated in the output plane, from which the true information can be accurately decoded and synthesized. It should be noted that if only partial secret keys or incomplete Morse code patterns are detected, misleading messages will result, thereby enhancing the overall security of the information transmission.

The proposed multi-DoF multiplexed D²NNs consist of three hidden layers that are trained using optical diffractive theory. In this architecture, the meta-atoms in each metasurface function as optical neurons, interconnected by the process of optical diffraction. According to the Huygens-Fresnel principle, each neuron (interacting with EM waves) in a hidden layer can be treated as a secondary spherical wave source. Consequently, the relationship between the electric field in the $(l+1)^{th}$ layer and that in the l^{th} layer can be expressed as:

$$E(r^{l+1}) = k(r^l) \iint_S E(r^l) \cdot f(r^{l+1} - r^l) dx dy \quad (1)$$

where $l = 1, 2, 3$ denotes the hidden layers, $E(r^{l+1})$ and $E(r^l)$ are the electric fields in the $(l+1)^{th}$ and l^{th} layers, respectively, $k(r^l) = A^l e^{i\phi^l}$ is the complex transmittance of the l^{th} layer. In addition, the impulse response $f(r^{l+1} - r^l)$ can be governed as:

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

where $R = \sqrt{(x^{l+1} - x^l)^2 + (y^{l+1} - y^l)^2 + (z^{l+1} - z^l)^2}$ and λ is the wavelength of the incident EM wave. Furthermore, the optimization of the network (*i.e.*, the minimization of the loss function) is

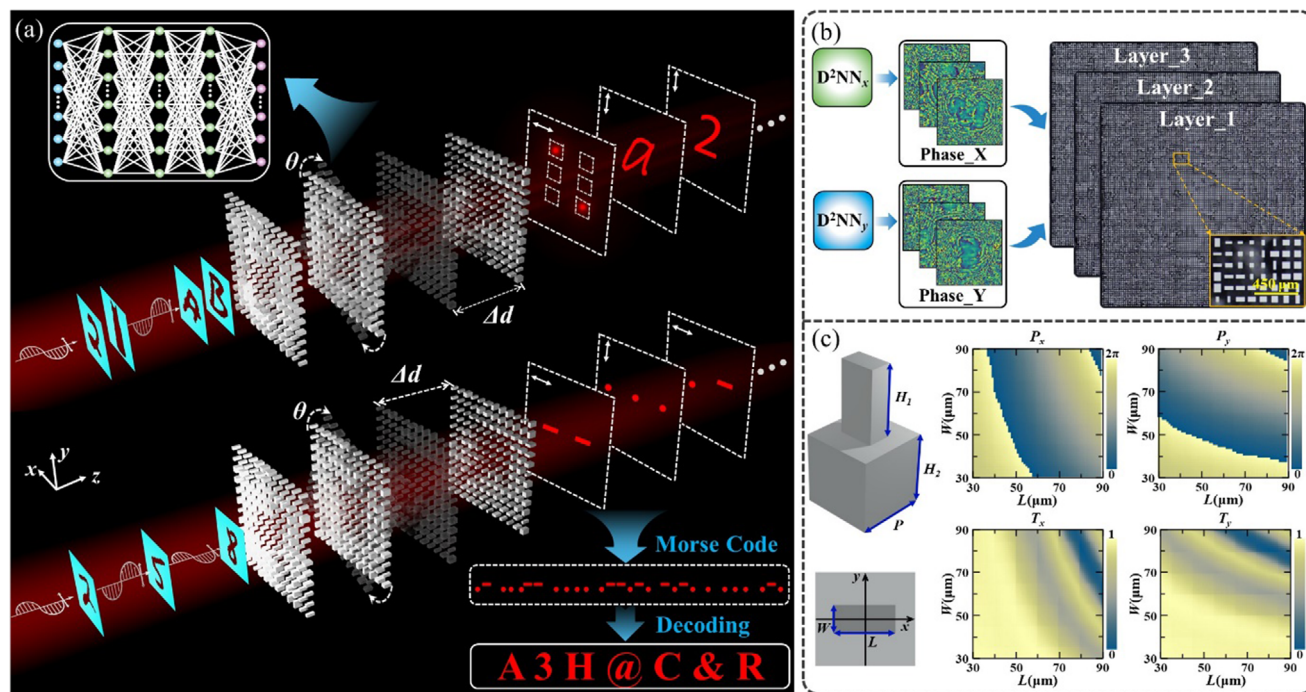


Figure 1. Schematic of multi-DoF D²NNs and its design methodology. a) Schematics of D²NNs with versatile functions for classification and image transformation (top), and the extended application in information encryption (bottom). b) Design schematic and representative samples of multi-DoF D²NNs. c) Phase variations and transmission coefficients of meta-atoms as a function of their lateral dimensions.

performed using an error backpropagation algorithm combined with the random descent optimization approach.^[15]

Deep learning is employed to jointly optimize the integration of polarization, distance, and rotation for multi-DoF diffractive computing and information encryption. After training the D²NNs, the phase profiles of each hidden layer are extracted from the optimized networks. As shown in Figure 1b (left panel), for the incidence of *x*- and *y*-polarized terahertz (THz) waves, the multi-DoF D²NN_{*x*} and D²NN_{*y*} enable the multiplexing of polarization, distance, and rotation channels for multidimensional parallel-computing. The phase profiles of D²NN_{*x*} and D²NN_{*y*} are independently embedded into the horizontal and vertical dimensions of the three hidden layers, as shown in Figure 1b (right panel). Figure 1c presents the phase changes and transmission coefficients for *x*- and *y*-polarized THz waves at 0.7 THz. By selecting the optimized structural parameters, we design three-layer metasurfaces with size-variable meta-atoms (Figure 1b) to construct the physical networks.

2.2. Multi-DoF D²NNs for Single-Digit/Fashion Product Classification and Image Transformation

As a guiding study, we propose a three-layer metasurfaces approach for classifying digits and fashion products under *x*-polarized THz illumination by simply varying the distance between the physical networks, as shown in Figure 1. Each metasurface consists of 120 × 120 meta-atoms, which serve as a 120 × 120 neuron array. By jointly training on handwritten digits from the Modified National Institute of Standards and Technology

(MNIST) dataset and fashion products from the Fashion-MNIST, we extract polarization- and distance-dependent phase profiles from the D²NNs. The detailed design principle of the multi-DoF D²NNs is provided in Section S1 (Supporting Information). Consequently, recognition of both handwritten digits and fashion products is achieved by adjusting the distance between the physical networks for *x*-polarized THz waves. To demonstrate the dual-function classification, we selected the handwritten digits “1”, “2” and “3” for digit classification, and the fashion products “Dress”, “Coat”, and “Sneaker” for simultaneous recognition. Accordingly, the output plane of our network contains six discrete detection regions, with the first (second) column predesigned for digit (fashion product) classification. As shown in Figure 2a, for *x*-polarized THz waves, the output electric fields after processing the digit pattern (“1”) propagate through the three hidden layers and are primarily focused on the top-left region when the distances are set to *d*₁ = 5 mm, *d*₂ = 10 mm, *d*₃ = 10 mm, and *d*₄ = 5 mm. This indicates that the handwritten digit “1” is accurately identified by our D²NNs. The simulated and experimental output energy maps in Figure 2a reveal the highest energy distribution located at the region labeled “①”, further confirming the correct recognition of the digit “1”. In general, the experimental measurements agree well with the simulated results, except for a slight discrepancy in the energy/field distributions, which can be attributed to experimental and fabrication errors. When the input patterns are switched to digits “2” and “3”, the diffractive fields are located on the middle-left and bottom-left regions, respectively, with the measured output-energy distributions matching the diffractive fields and the simulated results.

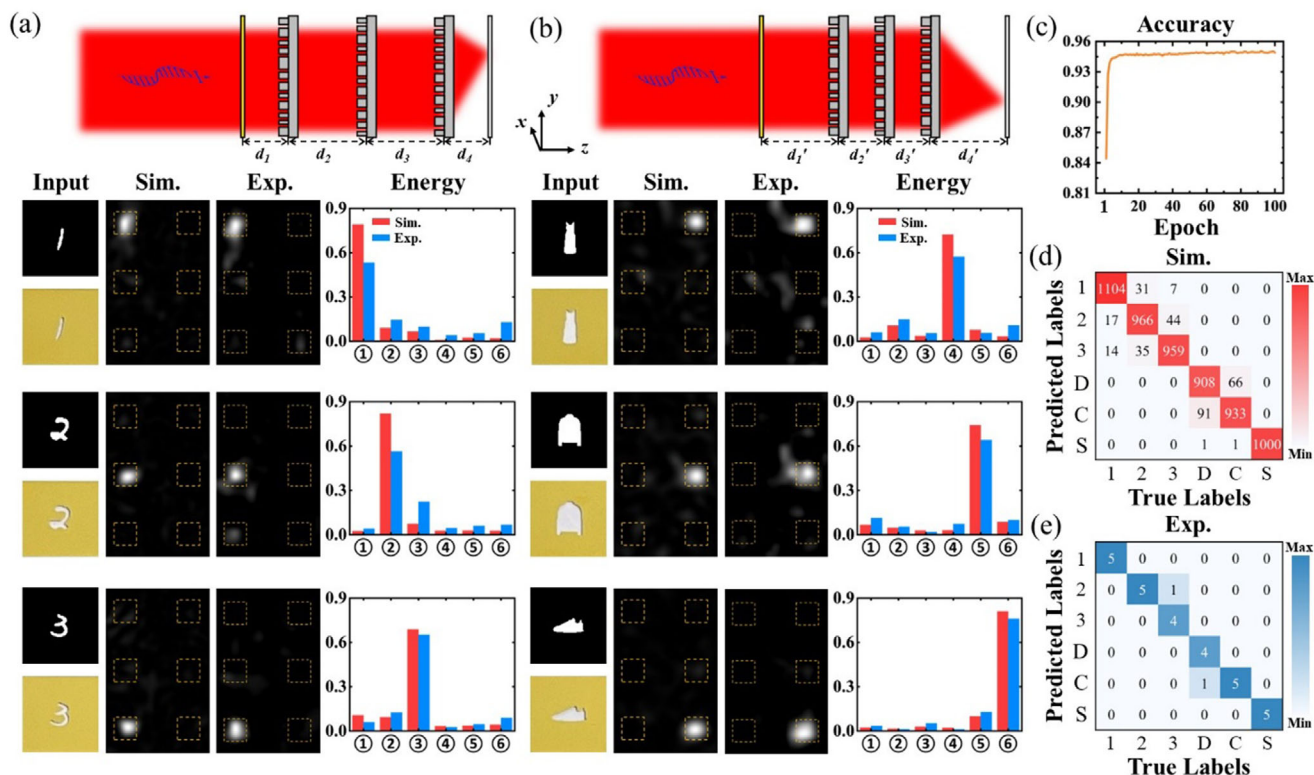


Figure 2. Simulated and experimental results of stretchable D²NNs under the *x*-polarized incidence. a) Schematic illustration, digit input patterns, corresponding electric field intensity distributions and energy distribution maps in the output plane for the digit classification with distances $d_1 = 5$ mm, $d_2 = 10$ mm, $d_3 = 10$ mm, and $d_4 = 5$ mm. b) Schematic illustration, fashion-product patterns, corresponding electric field intensity distributions and energy distribution maps in the output plane for the fashion product classification with distances $d_1' = 10$ mm, $d_2' = 5$ mm, $d_3' = 5$ mm, and $d_4' = 10$ mm. c) Training accuracy for the joint training of digits and fashion products. (d) and (e) Calculated and measured confusion matrices for digit and fashion product classification. The labels ①–⑥ correspond to “1”, “2”, “3”, “Dress”, “Coat”, and “Sneaker”, respectively, with “D”, “C”, and “S” representing “Dress”, “Coat”, and “Sneaker”.

To show the versatility and high performance of our proposed D²NNs, we adjusted the distances between the input plane, hidden layers, and output plane to $d_1' = 10$ mm, $d_2' = 5$ mm, $d_3' = 5$ mm, and $d_4' = 10$ mm, to enable fashion-product classification. Under *x*-polarized THz illumination, the diffractive fields after the fashion pattern (“Dress”) and the physical network are focused on the top-right region of the output plane, as shown in Figure 2b. Similarly, for the input patterns “Coat” and “Sneaker”, the diffractive fields are directed to the middle-right and bottom-right regions, respectively. The simulated and measured output electric-field intensity distributions in Figure 2b show good agreement with the expected diffractive field patterns. The corresponding energy distribution is defined as $P_{\text{sub}n}/P_{\text{total}}$, where $P_{\text{sub}n}$ is the sum of the energy in the n^{th} recognition region, and P_{total} is the energy across all recognition regions (Section S2, Supporting information). Figure 2c shows the test accuracy calculated over 100 periods, reaching 95%. The confusion matrices in Figs. 2(d) and 2(e) demonstrate calculated and measured test accuracies of 95% and 93.3%, respectively, indicating excellent agreement between simulation and experiment. To further illustrate the classification capabilities, we separately demonstrate fashion-product classification in channel 1 (with $d_1 = 5$ mm, $d_2 = 10$ mm, $d_3 = 10$ mm, $d_4 = 5$ mm) and digit classification in channel 2 (with $d_1' = 10$ mm, $d_2' = 5$ mm, $d_3' = 5$ mm, $d_4' = 10$ mm),

respectively (Section S3, Supporting information). Moreover, owing to the inherent resilience of D²NNs, our multi-DoF D²NNs demonstrate effective operation over a broad bandwidth. Detailed discussions on this aspect are provided in Supporting Information Section S4 (Supporting Information). Furthermore, the full classification results for all digit and fashion product classification under *x*-polarized incidence are shown in Section S5 (Supporting information).

In addition to the *x*-polarized channel, our physical networks enable versatile functionalities in the *y*-polarized channel, as shown in Figure 3. It should be noted that the three hidden layers in Figure 3 are identical to those in Figure 2, but they are under the illumination of *y*-polarized THz waves. Unlike the classification function in the *x*-polarized channel, the *y*-polarized channel achieves multiple image transformation functions based on the rotation operation. As shown in Figure 3a for the fixed distances of $d_1 = 5$ mm, $d_2 = 10$ mm, $d_3 = 10$ mm, and $d_4 = 5$ mm, the transmitted electric fields from an input pattern “A” are processed by the physical networks, resulting in the diffractive fields in the output plane that are transformed into the digit “1” under the illumination of the *y*-polarized THz waves. For the input patterns of Letters “B” and “C”, the output diffractive fields are converted into the digits “2” and “3”, respectively. Furthermore, when the physical network distances remain fixed ($d_1 = 5$ mm, $d_2 = 10$ mm,

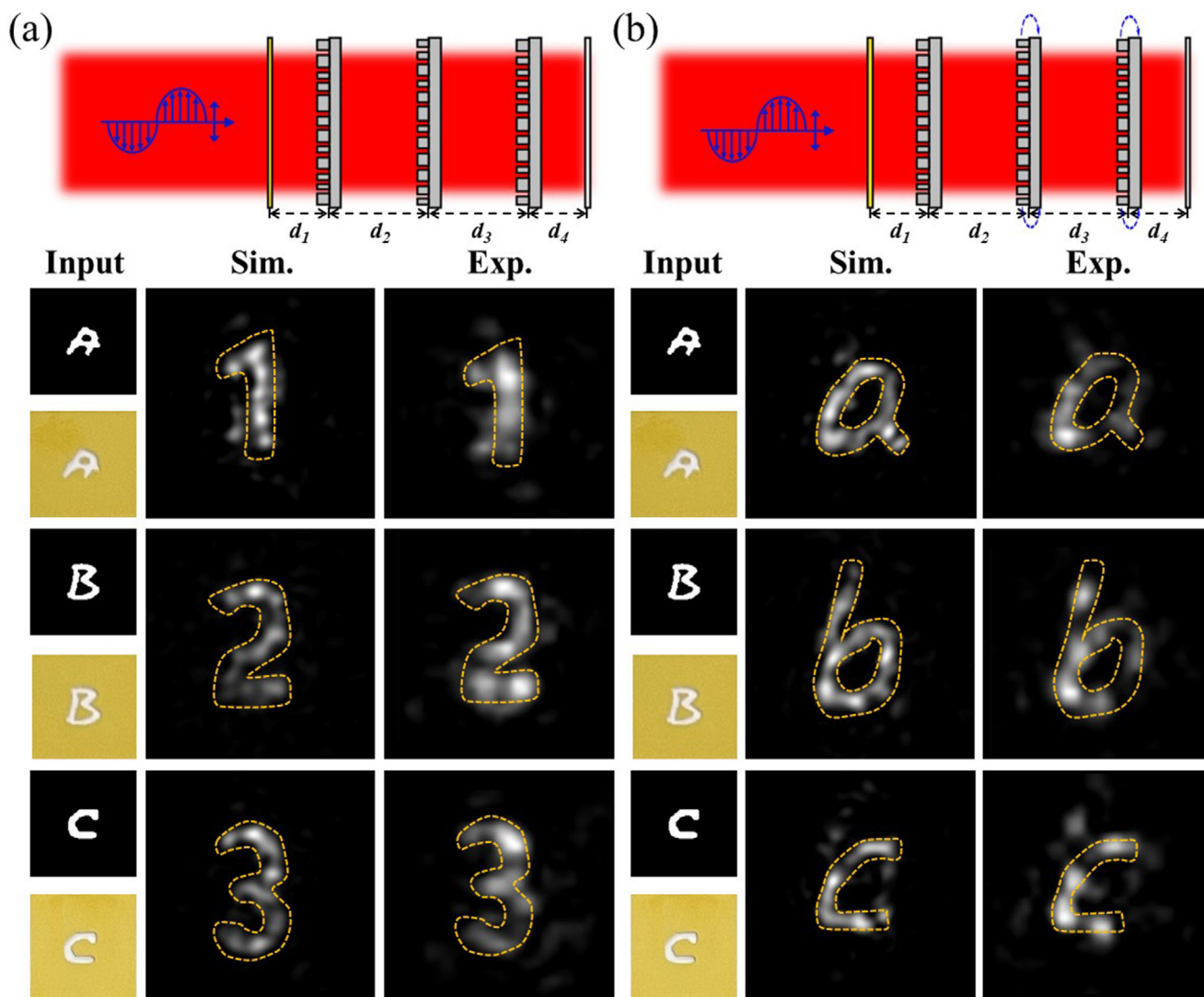


Figure 3. Simulated and experimental results of rotatable D²NNs under the γ -polarized incidence ($d_1 = 5$ mm, $d_2 = 10$ mm, $d_3 = 10$ mm, and $d_4 = 5$ mm). a) Schematic illustration, letter input patterns, and corresponding electric field intensity distributions in the output plane for image transformation without additional rotation. b) Schematic illustration, letter input patterns, and corresponding electric field intensity distributions in the output plane for image transformation with the rotation of the second and third metasurfaces.

$d_3 = 10$ mm, $d_4 = 5$ mm) but the second and third hidden layers are rotated anticlockwise with an angle of 180° , a different image transformation is obtained. In the configuration, the same input patterns “A”, “B”, and “C” are transformed into the lowercase characters “a”, “b”, and “c”, as shown in Figure 3b. Our approach can be extended to incorporate two orthogonal helical channels in combination with distance and rotation channels to enable both digit/fashion-product classification and image transformation. The corresponding simulation results are provided in Sections S6 and S7 (Supporting Information). To showcase the high-capacity processing capability of our designed D²NNs, we provide numerical demonstrations of image transformation for ten different input patterns in Section S8 (Supporting Information). In addition, the integration of distance and rotation DoFs in each polarization channel with extended functionalities (i.e., multiple logical operations) is further demonstrated in Section S9 (Sup-

porting Information). To further demonstrate the generalization capability of multi-DoF D²NNs, we present calculated results using various handwritten letter inputs in Section S10 (Supporting Information) and analyze the impact of input noise on output fidelity in Section S11 (Supporting Information). Additionally, we discuss the effect of rotation on polarization-dependent performance in Section S12 (Supporting Information).

2.3. Multi-DoF D²NNs for Dual-Digit/Fashion Product Classification and Logic Operators

To characterize the multi-task processing functionality of our designed multi-DoF D²NNs, we demonstrate dual-digit and dual-fashion-product classification in the x -polarized channel (Figure 4). In this case, the D²NNs are trained using dual-task

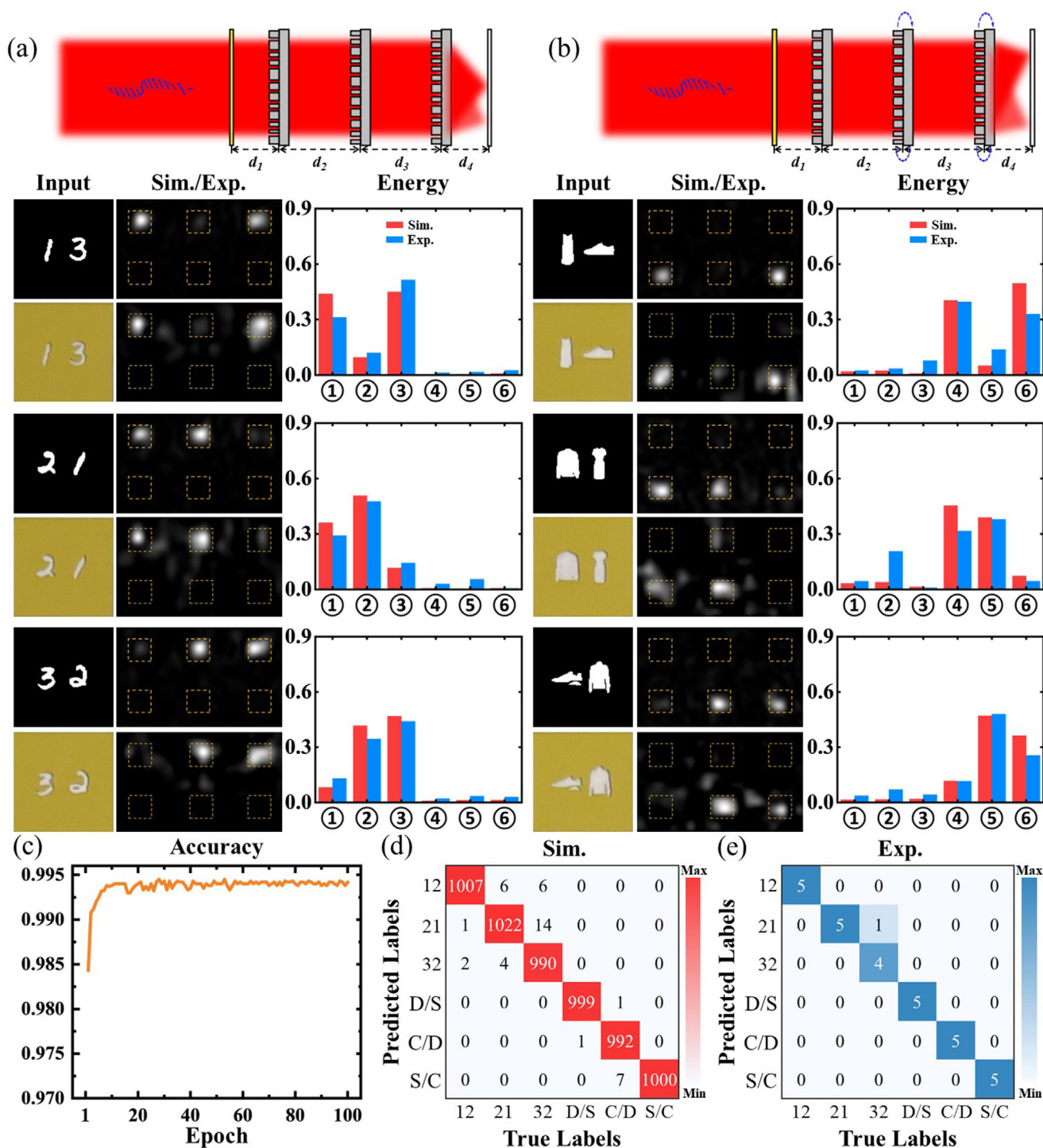


Figure 4. Simulated and experimental results of stretchable D²NNs under the x-polarized incidence ($d_1 = 5$ mm, $d_2 = 10$ mm, $d_3 = 10$ mm, and $d_4 = 5$ mm). a) Schematic illustration, digit input patterns, corresponding electric field intensity distributions, and energy distribution maps in the output plane for dual-digit classification. b) Schematic illustration, digit input patterns, corresponding electric field intensity distributions, and energy distribution maps in the output plane for the dual-fashion-product classification with the rotation of the second and third metasurfaces. c) Test accuracy for the joint training of dual-digit and dual-fashion-product tasks. d,e) Calculated and measured confusion matrices for dual-digit and dual-fashion-product classification. The labels ①–⑥ correspond to “1”, “2”, “3”, “Dress”, “Coat”, and “Sneaker”, respectively, while “D/S”, “C/D”, and “S/C” represent the combined classes “Dress and Sneaker”, “Coat and Dress”, and “Sneaker and Coat”.

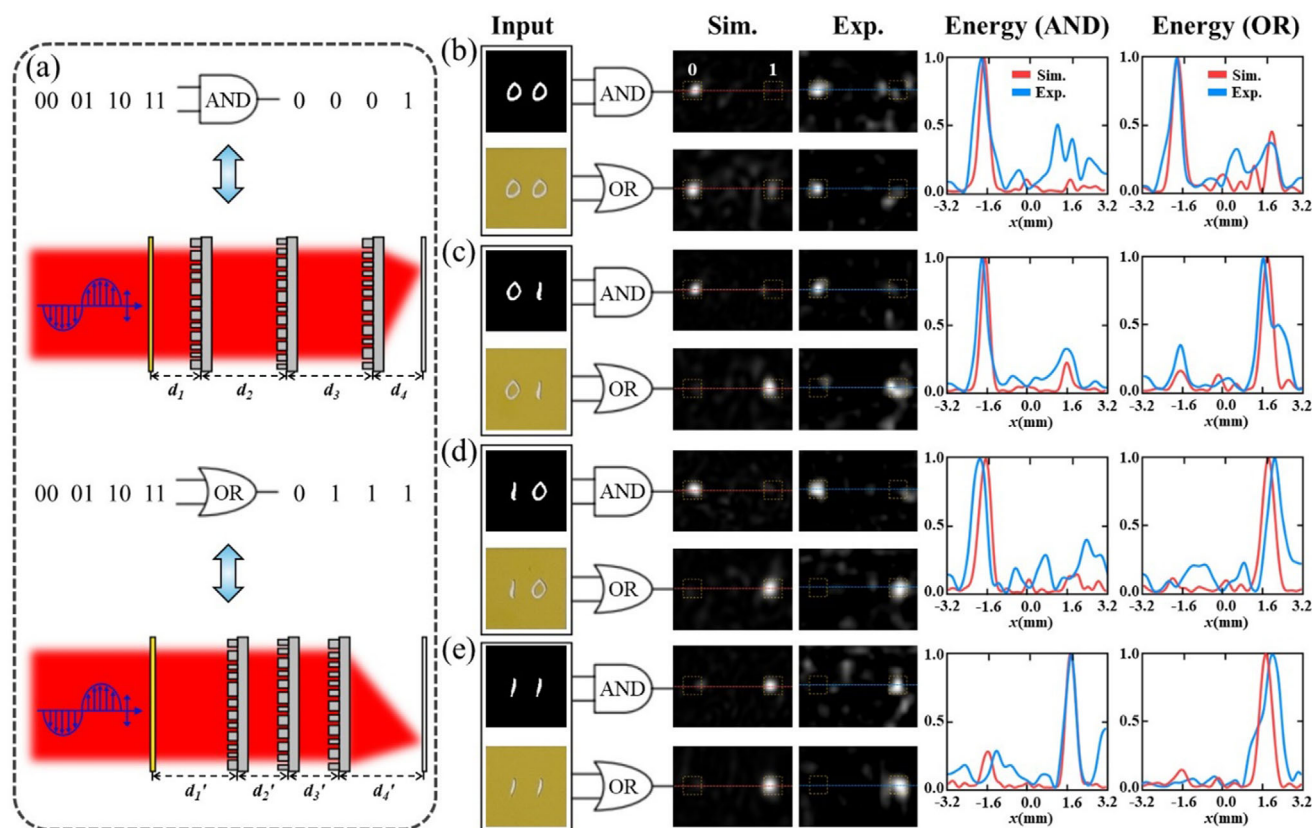


Figure 5. Simulated and experimental results of logic operators based on rotatable D²NNs under the γ -polarized incidence. a) Schematics illustration of the “AND” and “OR” logic operators. b–e) Electric field intensity distributions in the output plane and the electric field intensity at $y = 0$ for the input patterns “00” (b), “01” (c), “10” (d), and “11” (e). The distances are $d_1 = 5$ mm, $d_2 = 10$ mm, $d_3 = 10$ mm, $d_4 = 5$ mm and $d_1' = 10$ mm, $d_2' = 5$ mm, $d_3' = 5$ mm, $d_4' = 10$ mm.

inputs (*i.e.*, dual-digit or digit-fashion-product). By jointly training the network on the dual-digit and digit-fashion-product tasks with different distances between the three hidden layers, the optimal phase profiles are extracted and then encoded into the three-layer metasurfaces, resulting in a stretchable D²NN to process multiple tasks simultaneously. For example, when x -polarized THz waves illuminate the input dual-digit pattern “13” (with distances $d_1 = 5$ mm, $d_2 = 10$ mm, $d_3 = 10$ mm, $d_4 = 5$ mm), the diffractive fields emerging from the network are focused into the top-left and top-right discrete regions, indicating that the digits “1” and “3” are correctly identified (Figure 4a). For input patterns “21” (or “32”), the diffractive fields after the physical networks are focused into the top-left and top-middle regions (or top-middle and top-right regions), confirming the accurate recognition of the input dual-digit. The corresponding energy distribution maps closely match the diffractive field distributions in the output plane. When the distances between layers remain fixed, but the second and third layers are rotated either anticlockwise or clockwise by 180°, the network is reconfigured for dual-fashion-product classification, as shown in Figure 4b. For instance, with x -polarized THz wave illumination, input pairs such as “Dress and Sneaker”, “Coat and Dress” or “Sneaker and Coat” yield focused diffractive fields at the “bottom-left and bottom-right” or “bottom-left and bottom-middle” or “bottom-middle and bottom-right” regions of the output plane, respectively. The energy distri-

bution maps in Figure 4b are consistent with the diffractive field. The test accuracy calculated over 100 periods is 99.3% (Figure 4c), while the accuracies of confusion matrices in the simulation and experiment are 99.3% and 96.7%, respectively (Figure 4d,e). Further numerical demonstrations of multi-task, multi-DoF D²NNs with a broader range of input patterns are shown in Section S13 (Supporting Information). The classification of real-world images can be also implemented but with reduced test accuracies due to information loss from RGB-to-grayscale conversion (Section S14, Supporting Information). Nevertheless, these results confirm the scalability of our framework for more complex real-world datasets.

In addition to multi-target classification, the stretchable D²NNs in the γ -polarized channel can be further designed to implement other functionalities such as logic operators. As shown in Figure 5, the “AND” logic function is realized with distances $d_1 = 5$ mm, $d_2 = 10$ mm, $d_3 = 10$ mm, and $d_4 = 5$ mm, while the “OR” logic function is achieved with $d_1' = 10$ mm, $d_2' = 5$ mm, $d_3' = 5$ mm, $d_4' = 10$ mm. For the input of dual digits “00”, the γ -polarized electric fields after the input pattern are processed by our logic operators, leading to diffractive fields focused on the middle-left region of the output plane, demonstrating both “AND” and “OR” functionalities, as shown in Figure 5b. When the input dual digits are “01”, the output diffractive fields appear in the middle-left region for the “AND” operator and in the

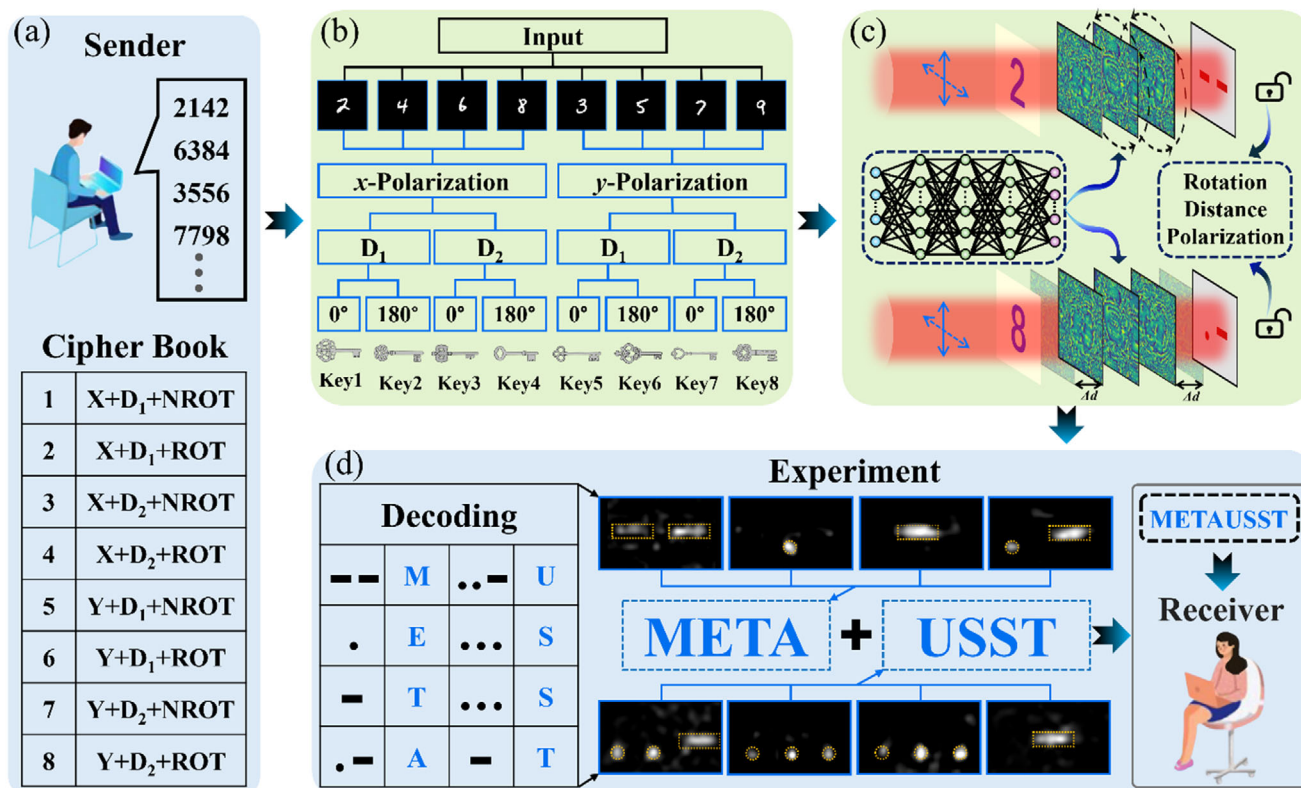


Figure 6. Multi-DoF D²NNs for high-security information transformation. a) Schematic of the sender transmitting large volumes of information. b) The information from the sender is assigned into different channels according to a pre-established cipher book. c) Schematic of the multi-DoF D²NNs for processing the input information. d) Diffractive field distributions on the output plane and the decoding of the Morse code at the receiver. Here, X(Y) represents the x-(y-)polarized channel. D₁ (D₂) corresponds to the distances $d_1 = 5$ mm, $d_2 = 10$ mm, $d_3 = 10$ mm, $d_4 = 5$ mm ($d_1' = 10$ mm, $d_2' = 5$ mm, $d_3' = 5$ mm, $d_4' = 10$ mm). ROT (NROT) indicates whether the second and third hidden layers are anticlockwise/clockwise rotated by 180° (ROT) or not (NROT).

middle-right region for the “OR” operator (Figure 5c). The “AND” and “OR” functionalities are further validated with dual-digit inputs “10” and “11” (Figure 5d,e).

2.4. Multi-DoF D²NNs for Information Encryption

All-optical information processing and computing enables high-efficiency information transmission and processing at the speed of light, which dramatically accelerates the development of communication networks and information technology. However, ensuring information security remains crucial when processing large volumes of data. Leveraging the proposed multi-DoF D²NNs, we have designed a high-security information transmission framework, as illustrated in Figure 6. As depicted in Figure 6a, a sender transmits various information, represented by a dataset of four digits. For example, “2142” can be considered as a dataset where the first (“2”) and third (“4”) digits denote the actual input information (or patterns) while the second (“1”) and fourth (“2”) digits represent the corresponding channels (e.g., channel 1 and channel 2) into which the input information (the first and third digits) is loaded. According to the cipher book, the first digit (“2”) is assigned to channel 1, meaning that it is encoded into the “X + D₁ + NROT” channel, while the second

digit (“4”) is loaded into the “X + D₁ + ROT” channel. Therefore, datasets such as “2142”, “6384”, “3556”, and “7798” are divided and loaded into different channels, each defined by specific polarization, inter-layer distances, and rotation or non-rotation of the second and third hidden layers, as shown in Figure 6b. Each channel functions as a secret key (key 1 to key 8 in Figure 6b) for encoding the information. In other words, the data transmitted by the sender consists of two parts: the input digits or patterns and the corresponding channel information used for encoding these patterns into their respective channels. The input digits are further encrypted by using the multi-DoF D²NNs, as shown in Figure 6c. Notably, each input digit in the correct channel is converted into its corresponding Morse code; any mismatch between the inputs and the assigned channels results in an incorrect Morse code, leading to the wrong information. In this way, the true information is locked by the input patterns and eight channels (secret keys). In addition, the partial information leakage from individual channels also produces an incomplete message, ensuring that one can obtain the full Morse code only by knowing the whole input patterns and the secret keys. As shown in Figure 6d, the input digits “2, 4, 6, 8, 3, 5, 7, 9” yield eight distinct Morse code sequences from the output plane. Decoding these sequences results in the final message “METAUSST” at the receiver. In consequence, the ciphertexts comprising a variety of

datasets of “2142”, “6384”, “3556”, and “7798” are finally loaded into different channels, transformed into Morse code, and ultimately decoded to the true information of “METAUSST”, showcasing high-security all-optical processing. It is important to note that traditional metasurface-based platforms offer only limited information encryption due to the constrained input format (e.g., plane waves). In contrast, our proposed multi-DoF D²NNs can process large volumes of information (*i.e.*, endless predefined ciphertexts as shown in Figure 6a), thus providing significantly enhanced capacity for information encryption. Based on this encryption method, the probability of correctly guessing all the true input information (*i.e.*, the eight secret keys) is $\approx 0.000006\%$ ($\approx (0.5^3)^8$), highlighting the high level of security provided by the multi-DoF encoding scheme. As a proof-of-principle, a high-security information transmission system with additional ciphertext inputs is numerically demonstrated in Section S15 (Supporting information).

3. Discussion

Previous studies have primarily focused on single-DoF multiplexing (*i.e.*, polarization, distance, or rotation) to enhance the functionality of D²NNs. In contrast, our approach integrates multi-DoFs into the D²NN framework, significantly enhancing the system's task-handling capacity. Compared to single-DoF implementations, the multi-DoF architecture offers additional control dimensions that not only improve information security but also enable high-capacity, secure information transmission and data exchange. By embedding polarization, distance, and rotation channels into a unified D²NN platform, the processor is capable of handling diverse and complex optical inputs, leading to a substantial improvement in overall computational throughput. However, the current implementation has practical limitations—most notably the requirement for physical adjustment of the distance and rotation channels, which constrains simultaneous multi-task execution. To address this, future architectures could incorporate removable and rotatable holders or automated tuning mechanisms to enhance both multi-tasking speed and operational flexibility.

Unlike previous optical encryption strategies, our approach allows large volumes of input data to serve as part of the encryption key, modulated through multi-DoF control in the D²NN. This concept introduces a new paradigm for scalable optical storage, where massive information sets can be securely processed and retained. Moreover, our all-optical multi-DoF D²NN platform is expected to be compatible with fiber-integrated technologies,^[51] offering promise for low-energy, high-capacity information processing in future optical communication systems.

In addition, the energy efficiency for D²NNs is another issue that hinders the fast development of this field, since it is $\approx 16\%$ for the three-layer D²NNs.^[15] Thus, we need to develop a high-power light source to efficiently perform the unique functionalities of D²NNs. In a word, the multi-DoF D²NNs developed in this work provide a flexible platform (by integrating polarization, distance, and rotation channels) that offers a novel approach for advancing optical storage and multifunctional integrated devices.

4. Conclusion

In conclusion, we have proposed and experimentally demonstrated multi-DoF D²NNs that integrate polarization, distance, and rotation to implement versatile inference tasks and high-security information encryption. Our approach employs a metasurface-based approach, leveraging three-layer metasurfaces with tailored spatial distances and rotation angles to construct the multi-DoF D²NNs. We first demonstrated single-digit and fashion product classification as well as image transformation by jointly training the handwritten digits and fashion products. The phase profiles for classification were encoded into the x -polarized channel, while those for image transformation were embedded into the y -polarized channel. To further showcase the multi-task processing capability, we implemented dual-digit and dual-fashion product classification alongside logic operations. Moreover, we designed an all-optical high-security information transmission system that can transform large volumes of input information across different channels into Morse code, from which the true information can be decoded by correctly combining the secret keys. Overall, our multi-DoF D²NNs demonstrate high-capacity capabilities across versatile channels, paving the way for advanced applications in high-speed communication, privacy protection, and high-capacity information processing.

5. Experimental Section

Training: The three-layer D²NNs were constructed using Python (v3.9.16) and TensorFlow (v2.6.0, Google Inc.) on a Windows 10 system (Microsoft). The hardware system consists of two Intel(R) Core (TM) CPU i7-12700H @ 2.20 GHz central processing unit (CPU, Intel Inc.), 512 GB RAM, and a GeForce RTX 3060 Ti graphical processing unit (GPU, Nvidia Inc.). Each training epoch for the proposed DNN takes ≈ 24 s. An early stopping mechanism was applied to terminate the training when the validation loss improvement falls below 10^{-3} over 10 consecutive epochs. Under this condition, the training process typically completes within 100 epochs, requiring ≈ 40 min. For digit and fashion product classification tasks, the MNIST and FMNIST datasets were used. The training was performed with a batch size of 8 for 100 epochs using the Adam optimizer with an initial learning rate of 0.001. The loss function was defined as the mean square error between the output field intensity and the target output field intensity in the last hidden layer. The phase profiles (that were encoded into the metasurfaces) of the hidden layers for network training were updated by leveraging the stochastic gradient descent algorithm.

Fabrication: For the fabrication process, a 1000- μm -thick intrinsic silicon wafer ($<100>$, resistivity > 5000 ohm, from HF-Kejing) was first cleaned using an ultrasonic bath. A 7–8 μm thick AZP4620 photoresist film was then spin-coated onto the silicon wafer and baked on a hotplate at 100 °C for 1 min. The photoresist was patterned using an IMP SF-100 mask aligner. After development, the resulting micro-pillar structures in the resist were hard-baked at 100 °C for 2 min to improve adhesion and thermal stability. The pattern silicon wafer was subsequently etched using the DRIE process based on the Bosch method, employing SF₆ and C₄F₈ gases for ≈ 95 min. Finally, the rectangular meta-atoms were formed after removing the photoresist.

Experimental Setup: The diffraction field distributions in the output plane were measured using a near-field scanning THz time-domain spectroscopy microscopy system (NSTDSM). The experimental setup and data processing methods were provided in Section S16 (Supporting Information). A femtosecond laser beam with a central wavelength of 1560 nm was split into two parts. One beam was coupled into an optical fiber and then directed into a photoconductive antenna emitter to generate THz waves. The other beam passes through a periodically polarized lithium niobate

(PPLN) crystal, generating a 780 nm laser beam that was subsequently focused into a THz tip. The THz tip was mounted on a 3D translation stage, while the samples (*i.e.*, the three-layer metasurfaces and input pattern) were fixed. By scanning the THz tip after the three hidden layers, the diffraction light field distribution behind the samples can be achieved.

Supporting Information

Supporting Information is available from the Wiley Online Library or from the author.

Acknowledgements

X.Z. and Y.Z. acknowledge the National Natural Science Foundation of China (61988102, 62271320, and 61871268), the Science and Technology Commission of Shanghai Municipality (21S31907400), the Key Research and Development Plan of Ministry of Science and Technology (Grant No. 2023YFF0719200), and the Shanghai Municipal Science and Technology Commission (22JC1400200).

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

X.Z., F.D. and Y.Z. initiated the idea. T.Z. conducted the numerical simulations. T.Z. and G.W. performed the measurements. X.Z. and F.D. prepared the manuscript. X.Z., F.D. and Y.Z. supervised the project. All the authors discussed and analyzed the results.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Keywords

all-optical processor, diffractive deep neural networks, high-security information transmission, information encryption, metasurfaces, multi-DoF

Received: April 1, 2025
Revised: June 4, 2025
Published online: June 13, 2025

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