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Deep learning for digital holography: a review

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Abstract: Recent years have witnessed the unprecedented progress of deep learning applications in digital holography (DH). Nevertheless, there remain huge potentials in how deep learning can further improve performance and enable new functionalities for DH. Here, we survey recent developments in various DH applications powered by deep learning algorithms. This article starts with a brief introduction to digital holographic imaging, then summarizes the most relevant deep learning techniques for DH, with discussions on their benefits and challenges. We then present case studies covering a wide range of problems and applications in order to highlight research achievements to date. We provide an outlook of several promising directions to widen the use of deep learning in various DH applications.

1. Introduction

Digital holography (DH), which combines holographic imaging with digital image processing, has made remarkable progress in recent years [1]. It uses electronic sensors to replace the traditional holographic dry plate to record holographic images, and computes the optical propagation to reproduce the wavefront distribution of the original object in the reconstruction process. Mathematically, an object $O(x, y)$ and reference $R(x, y)$ with complex amplitudes can be expressed as

$$O(x, y) = A_O(x, y)e^{-j\phi_O(x,y)}, \tag{1}$$

$$R(x, y) = A_R(x, y)e^{-j\phi_R(x,y)}, \tag{2}$$

where $A_O(x, y)$, $A_R(x, y)$ and $\phi_O(x, y)$, $\phi_R(x, y)$ are amplitude and phase of the object wave and reference wave. On the imaging surface, the object light and the reference light are coherently superimposed to form a hologram $H(x, y)$, which is expressed as $H(x, y) = |O(x, y) + R(x, y)|^2$. It can then be expanded into

$$H(x, y) = |R(x, y)|^2 + |O(x, y)|^2 + R^*(x, y)O(x, y) + R(x, y)O^*(x, y), \tag{3}$$

where $*$ represents the complex conjugate. The first two parts are the zero-order terms, while the third and fourth terms are the interference. By digitally processing the latter, the reconstructed image of the object can be obtained. For in-line DH systems, also known as Gabor DH, the reference light and object light pass through the same optical path and carry out coherent superposition on the detector. In an off-axis system, the optical paths of reference light and object light are separated, and this eliminates the twin image. The typical off-axis DH system includes the Michelson interferometer and the Mach-Zehnder interferometer.

As a rapidly developing imaging technology, DH has several main advantages. First, compared with optical holography, the use of a photoelectric imaging device eliminates the chemical processing of the dry plate in the holographic image reconstruction process. Furthermore, it can record the 3D morphological information of the object, enabling surface contour measurement and 3D reconstruction, especially for tiny objects. Moreover, because the holograms are already in digital form, the defects in the image such as noise, speckle, and aberration can be computationally

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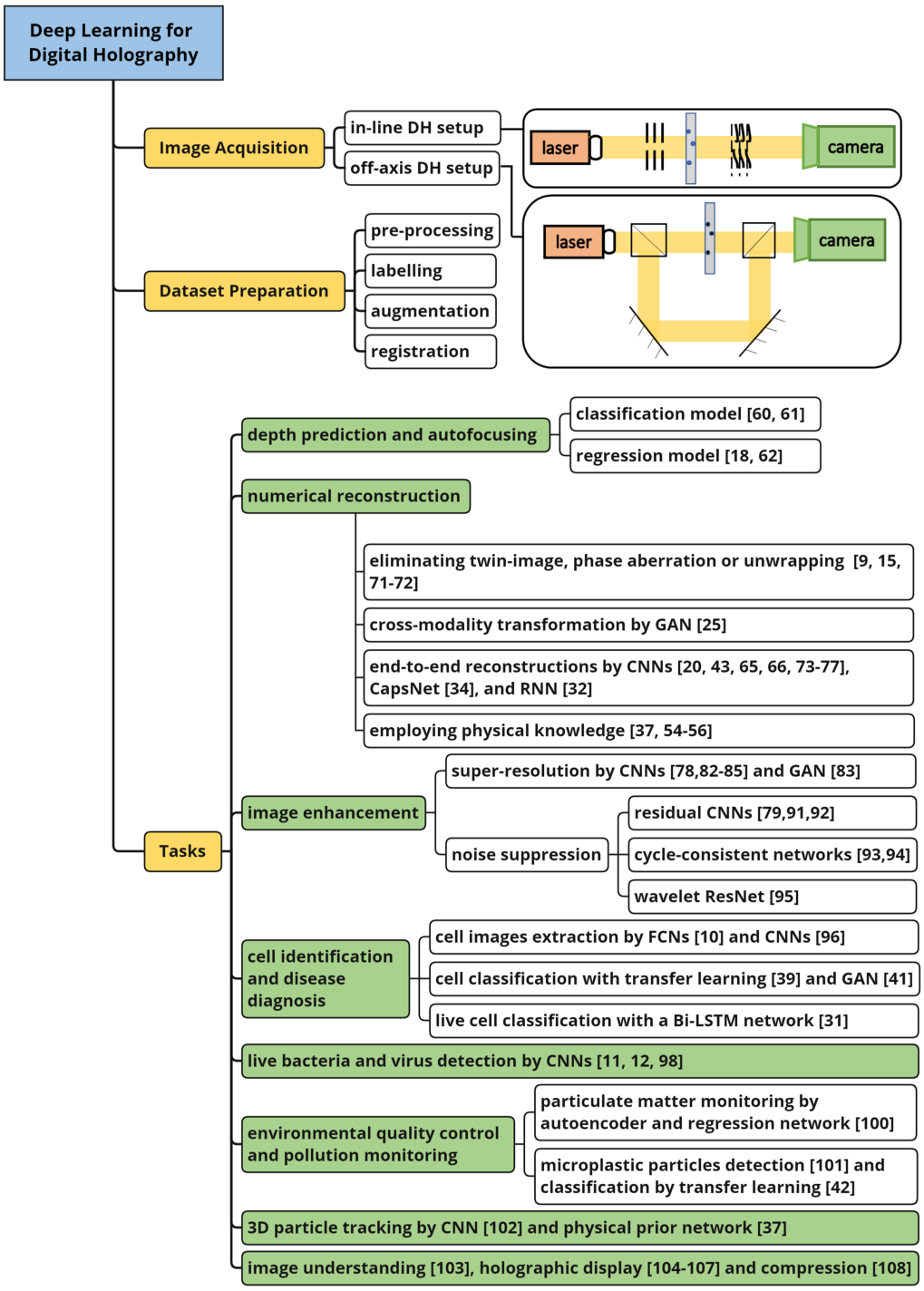

Fig. 1. The workflow of using deep learning to perform DH-related tasks.

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processed. In addition, DH can also be combined with other optical imaging technologies such as optical field imaging [2], optical coherence tomography [3], hyperspectral imaging [4], and so on. Nevertheless, DH has its own shortcomings. For example, the surface area of photoelectric devices is generally small, which limits the imaging range. The imaging resolution is greatly affected by the bandwidth of the light source, and a highly coherent light source is generally required.

Traditionally, holographic image processing has relied on classical methods derived from the explicit analytical formulation of the forward models. The recent progress of deep learning in solving a wide range of imaging problems has demonstrated its powerful capability in computational modeling. In 2015, an artificial neural network was trained to reconstruct the refractive index of 3D objects recorded by a holographic tomography system [5]. Since then, deep learning techniques have been increasingly applied to DH on various inverse problems such as reconstruction and super-resolution, as well as perception tasks such as detection and tracking. Figure 1 provides an illustration of a typical workflow in the field of digital holography.

This review is organized as follows. In Section 2, we give an overview of how deep learning is used for DH. We offer our perspectives on the benefits and possible pitfalls of applying deep learning in DH and discuss relevant models and algorithm strategies. We then summarize in Section 3 the recent research progress of deep learning in various specific DH applications. Finally, an outlook on future developments with deep learning in driving DH forward is provided in Section 4.

2. Overview of Relevant Deep Learning Techniques in DH

Deep learning is a computational technique that aims at mimicking the way our brain functions. It mainly uses deep neural networks (DNNs), consisting of a layered structure where information is encapsulated in connected neurons and passed along the layers [6]. DNNs extract valuable information from the data and learn effective features to achieve optimal outcomes in specific tasks. Training a DNN often involves gradient descent optimization, where parameters are learned by optimizing loss functions designed according to different tasks in the back-propagation step.

2.1. Benefits and Potential Issues

In DH, there are inverse imaging tasks, aiming at recovering spatial, spectral, and phase information from the wavefront of the object recorded in a hologram, and perception tasks, involving an understanding of the recorded information such as object recognition and detection. The latter is more related to computer vision, and in this review, our focus is on the former.

The classical techniques to solve inverse imaging problems often assume an explicit analytical formulation of the physics model, together with simplified approximations such as linearity. Deep learning can bypass the stringent requirements of known analytical models, and demonstrate a powerful modeling capability through training on input and output pairs. Furthermore, due to the ill-posed nature of inverse problems, physics-driven approaches often rely on heuristics in designing the regularization term [7]. Deep learning, on the other hand, can learn more robust priors in a non-parametric way, which can help to tackle problems with highly undersampled inputs. For example, multiple measurements are often required in phase recovery for in-line holography using traditional reconstruction methods, which limits the object to be quasi-static [8]. Deep learning enables single-hologram recovery after training on labeled image pairs [9].

Deep learning can also alleviate the stringent system requirements in the optical setup and compensate for the mismatches computationally. In addition, once the training process completes, deep learning allows for real-time reconstruction with fast inference. As for perception tasks [10–12], deep learning can shorten the time in sample pre-processing, eliminate many steps in image post-processing and reconstruction in the later stage, and also improve the accuracy.

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Generally speaking, deep learning can significantly improve the results in a wide range of holographic tasks, reduce the complexity of imaging experiments, and also facilitate new functionalities. However, there are still some potential problems when applying deep learning in DH-related tasks.

First is the lack of sufficient standard-compliant data. Due to rigorous experimental requirements, it usually needs extensive work to acquire enough holograms, not to mention accurately annotated datasets. Moreover, diverse types of DH systems with different optical setups lead to high variance among captured holograms [13]. It is challenging for DNNs to produce robust predictions over such variance.

Second, the complex nature of DH increases the difficulty of modeling the image formation process. The misinterpretation of jumps in the wrapped phase as edge structures is also a tricky problem in holographic image processing [14]. Hence, DNNs are expected to handle complex values and the cyclical nature of phases. Additionally, artifacts uncommon in natural images, such as speckles, phase aberrations, defocus noise, and twin-image, restrict the direct usage of DNNs from computer vision in DH-related tasks [15]. In addition, the captured holograms are of relatively large size and also rich in information. To fully exploit the rich information, one often favors deeper networks with more parameters and more complicated algorithms such as attention [16], while the large image size hinders the implementation of computational and memory intensive models.

The lack of interpretability of deep learning is also problematic for DH, particularly for medical applications. One might question the good experimental performance of DNNs as a coincidence rather than resulting from the correct modeling of the target problem. With no guarantee to obtain physically accurate results, troubleshooting can also be challenging. It severely hinders the application of deep learning in real-world DH tasks.

Overall, deep learning in DH applications is still at the exploratory stage, where most of the studies were within the last five years. Nevertheless, promising results encourage continuous exploration. Before detailed case studies, we will first briefly review both established and some emerging deep learning techniques used in DH.

2.2. Network Architectures

The performance of deep learning depends largely on network architectures, which determine how hierarchical information is passed from layer to layer. The DNNs implemented in DH are mostly tailored models derived from several widely used architectures summarized below and also presented in Fig. 2.

Convolutional neural networks (CNNs). Most deep learning studies in DH, including both inverse imaging and perception tasks, are implemented using CNNs. The core of CNNs lies in the convolutional layer, which performs convolution between the input image and the so-called kernels, i.e., small patches of different patterns, and encapsulates feature maps from such an operation. By adding skip connections to help compensate information loss along with the layers and mitigate the problems of difficult learning when the network gets deeper, U-Net, ResNet and DenseNet become leading CNN architectures in DH [17–19]. Both ResNet and DenseNet can also be combined with U-Net to form Res-UNet or Densely connected U-Net, which have been demonstrated to further improve performance in various DH applications such as holographic reconstruction [20], autofocus imaging [21], computer-generated holography [22], holographic imaging of 3D particle fields [23] and so on.

Deep generative models. The deep generative models capture distributions of training data and produce similar new samples. The most popular networks of this class used in DH are generative adversarial networks (GANs). GANs make use of two neural networks, known as generator and discriminator, in the learning process [24]. Specifically, the generator produces new samples based on the statistical distribution learned from real samples, while the discriminator

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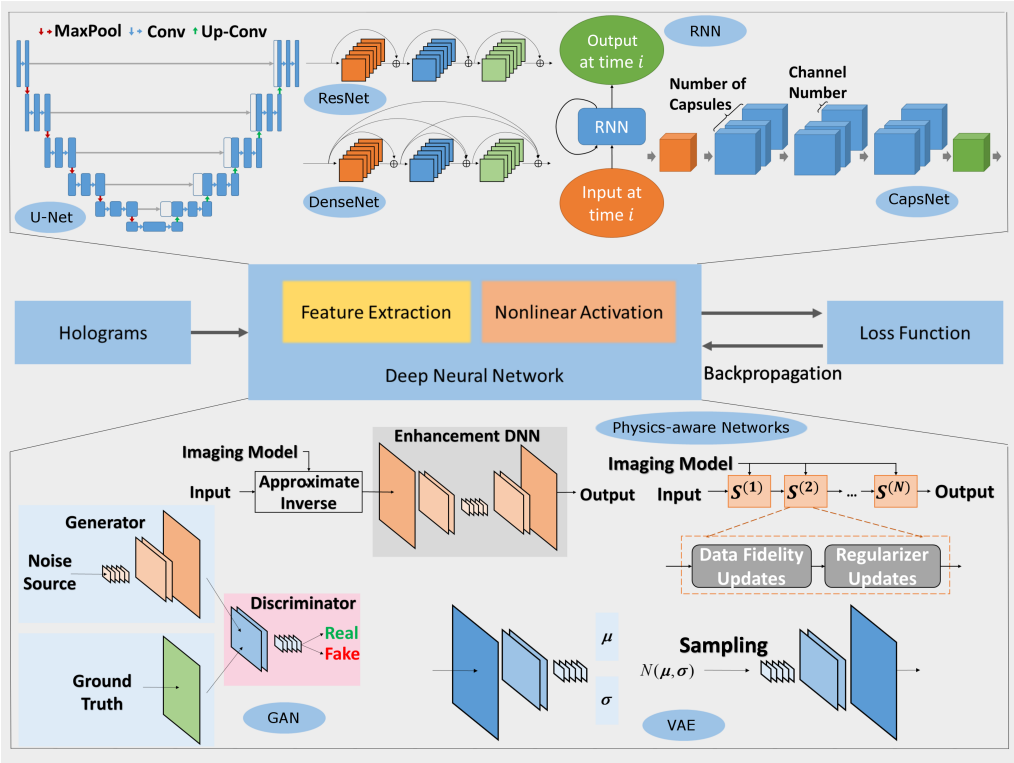

Fig. 2. General diagram of applying deep learning in DH with a selection of relevant networks. The upper box covers basic architectures of three commonly-used CNN networks (i.e., U-Net, ResNet and DenseNet), the recurrent neural network (RNN), and the capsule network (CapsNet). The lower box shows general structures of two main kinds of deep generative models, i.e., generative adversarial network (GAN) and variational autoencoder (VAE), and two popular ways of incorporating physical priors in physics-aware networks, i.e., cascading and unrolling.

attempts to distinguish between the generated samples and the real ones. In DH, GANs have been applied to enhance image quality [25], augment holographic datasets [26], and enable annotation-efficient learning approaches, such as unsupervised classification of live cells [27] and phase retrieval given unpaired holograms [28]. Another main kind of deep generative model is the variational autoencoder (VAE). It describes observations in latent space in a probabilistic manner under an encoder-decoder structure. It has been successfully implemented for hologram generation [29] and has also been combined with GANs to alleviate training difficulties for designing intelligent coding metasurface holograms [30].

Recurrent neural networks (RNNs). RNNs, distinguished from feed-forward networks like CNNs, refer to deep learning architectures where the output depends on both the current input and the previous output [6]. In particular, long short-term memory (LSTM) is one of the most popular RNNs that resolves the vanishing gradient problem and provides superior performance in the classification of video-rate holograms of live red blood cells [31]. It is worth noting that RNNs and CNNs are not exclusive. Recently, Huang *et al.* [32] demonstrated the success of

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applying a convolutional RNN under the GAN framework to perform both autofocusing and reconstruction using multiple holograms at different sample-to-sensor distances at the same time.

Capsule networks (CapsNets). CapsNets, proposed by Hinton and his colleagues [33], are considered as alternatives to CNNs. Owing to the vectorized form of neurons and the routing mechanism, capsule networks encode extra hierarchical spatial information of features and possess superior characteristics, such as equivariance to transformation, enabling powerful generalization capability of models to novel viewpoints. The study reported in [34] demonstrates that a residual capsule network based on encoder-decoder architecture can significantly reduce the number of parameters in holographic reconstruction.

Physics-aware networks. Recently, emerging studies attempt to incorporate the physics of different optical imaging systems into DNNs [30,35–37]. Besides the simple cascaded architecture that stacks the model-based approaches and enhancement networks in sequence, the emerging unrolled networks open up a new field of DNNs by mimicking the iterative operations in solving optimization problems [36]. They unroll iterations of classical optimization solvers into network layers and learn traditionally hand-picked hyper-parameters from data. In particular, a recent work [37] in DH has made an initial effort in unrolling the half-quadratic splitting method into a holographic reconstruction network for 3D particle imaging.

2.3. Strategies towards Data Challenges in Deep Learning

DNNs often require large-scale datasets with carefully labeled data pairs covering diverse real-world scenarios to enable sufficient supervised learning. The training strategies of most existing DNNs in DH fall into this category. Nevertheless, obtaining large datasets of annotated holograms for various applications, such as biomedical imaging, is very challenging or even impossible. As a result, studies have investigated deep learning approaches for processing datasets with insufficient data or annotations, including transfer learning, data augmentation, unsupervised learning, unpaired training, and untrained models.

Transfer learning. Derived from the need to apply deep learning into research fields lacking sufficient datasets, transfer learning emerged with the goal of transferring existing learned knowledge of source problems to some relevant target problems so as to alleviate the requirement of large training data. The basic principle behind this approach is that different image types often share similar low-level characteristics that are generally better learned with a bigger dataset. It has been demonstrated to be very effective in accelerating the speed of training convergence, preventing over-fitting, and therefore generating more accurate predictions [38]. With the remarkable success achieved by transfer learning, researchers have also applied it in DH, mostly in classification and detection tasks [39–42].

Data augmentation. Another solution to the problem of limited datasets is data augmentation. It has been widely used for various research topics in DH [18,20,43,44]. Contrary to transfer learning, data augmentation is a data-space solution that addresses this issue by directly increasing the size of the training dataset. The two main types of data augmentation techniques are transformations of available images and introducing new synthetic data. The former involves various image manipulations, including flipping, cropping, rotation, translation, and noise injection. These transformations are simple and work well in many cases. However, for some scenarios, such as tasks with too small and imbalanced datasets, these approaches are no longer suitable and may even introduce artifacts. Synthesis methods aiming at generating new training data have then emerged. Some recent DH studies use deep generative models to enlarge the dataset based on the distribution of available holograms or generate 3D poses from incorporating 2D images [45,46].

Unsupervised learning. Besides the limited size of datasets, insufficient annotation or ground truth images is also problematic. Thus, annotation efficient learning strategies have emerged. Unsupervised learning refers to approaches that train a model using only unlabeled data [47].

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The widely-used representative deep learning techniques include autoencoders, VAEs, and GANs, and they can extract task-related features and generate predictions from unlabeled data without supervision. Apart from the extreme cases, there are some circumstances where datasets with only inexact annotations or with a small portion of correctly labeled data are available. Weak supervision or semi-supervised algorithms can therefore be employed to leverage limited information during training [47]. The field of DH has employed unsupervised learning in very few research topics, including organization of cervical cells [27], computer-generated holography [48], and particle classification and sizing [49], but achieved promising results.

Unpaired training. The unpaired training is a newly emerged deep learning technique trying to address mapping across modalities with unpaired datasets. A recent deep learning method, CycleGAN [50], utilizes two GANs to form consistency constraints between a pair of cycle consistent functions. It is one of the first models to achieve image-to-image translation with unpaired images. In DH, this training method appears to be well suited, as pairing objects with their holograms can be challenging. Some studies have presented preliminary results in approaching holographic reconstruction with unpaired datasets [28,51].

Untrained models. The untrained, or unlearned, models are deep learning algorithms requiring no training beforehand. Deep image prior (DIP) [52] and deep encoder [53] are exemplar algorithms that apply untrained generative models to solve inverse problems given only raw measurements and the forward operators. Such feature makes them especially appealing for DH. Studies recently incorporate holographic imaging models and phase wrapping processes in untrained networks for reconstruction [54], phase imaging [55], and unwrapping [56], optimizing network parameters on a single measurement instead of a large labeled dataset.

3. Case Studies of Deep Learning Applications in DH

3.1. Depth Prediction and Autofocusing

A hologram, as intensity patterns produced by the interference of two wave beams, records the entire wavefront of the object. One often needs the exact axial position of the object before reconstruction. Hence, studies on autofocusing techniques have emerged for automatic distance detection. In applications involving continuous tracking of dynamic specimens or unstable environments with system disturbances, holographic autofocusing plays a critical role in the subsequent robust reconstruction of in-focus and high-quality images. Traditional computational methods handle autofocusing problems based on various types of metrics, including gradient [57], sharpness sparsity [58], local variance [59], and so on. Most of these methods employ a search on sequential reconstructions over a possible range of focus distances. They are generally computationally expensive and time-consuming.

The autofocusing problem is initially formulated as a classification task to be tackled by deep learning. The pioneering work presented by Pitkääho *et al.* [60] successfully employs two CNN-based architectures, AlexNet and VGG16, to determine the focus positions of canine kidney cell clusters using off-axis digital holographic microscopy (DHM). They determine the ground truth by manually measuring the sharpest outer edge of the reconstructed holograms at different depths. No numerical propagation is required. To remove the zero-order and twin terms, holograms undergo a preprocessing step before feeding to the network. Ren *et al.* [61] later also demonstrate the effectiveness of considering autofocusing as a classification task tackled by a tailored CNN without any prior knowledge of the DH system. Imaging experiments are restricted to a set of discrete distances to obtain classes (object distances).

For more realistic situations requiring continuous depth estimates, several methods adopt regression models. In [18], both amplitude and phase-only objects imaged at 10 and 5 different distances, respectively, have been used for demonstrating the accuracy of a CNN regression model in depth prediction. The robustness has been evaluated with different exposure times, incident angles, and axial distances outside the training set. Shimobaba *et al.* [62] make additional

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improvements by using the power spectrum of in-line holograms (simulation of amplitude-only images) as the input and achieve accurate depth prediction with millimeter precision with hologram reduced to 1/8 of its original size. The use of the power spectrum helps simplify the CNN regression model and thus shorten the training and inference time. Some works have then combined the autofocusing and reconstruction by performing both tasks at the same time via a Res-UNet or a convolutional RNN [32,63]. More details will be reviewed in the following section of holographic reconstruction. Overall, deep learning methods have achieved the highest accuracy in depth prediction and presented significant improvements in inference speed.

3.2. Numerical Reconstruction

Numerical reconstruction in DH refers to reconstructing the whole wavefront information of the imaged scene, including both amplitude and phase recovery, from holograms captured by an electronic sensor [13]. In order to obtain high-quality reconstructions, extra steps are often required. For instance, recording multiple measurements for the same object in multiple planes, or with reference light of different phase retardation, are common ways for twin-image suppression in in-line DH [67]. Moreover, directly calculating the phase from the complex exponent can be seriously affected by aberrations, such as tilt phase due to off-axis geometry, and also results in wrapped phase. Therefore, algorithms aiming to unwrap the phase and compensate for the aberrations have been used, including minimum-norm [68] and temporal methods [69].

Many studies have explored the feasibility of using deep learning techniques to tackle these problems. One can generally categorize them into multi-step or one-step reconstructions. The former refer to those leveraging deep learning networks to replace one step of the multi-step process, such as eliminating twin-image on the intermediate reconstructions obtained from conventional algorithms [9] or performing phase aberration [15] and unwrapping [64,70,71] (Fig. 3(a)). For example, Rivenson *et al.* [9] perform holographic reconstruction by first recovering the complex wavefront from an in-line hologram based on free space back-propagation and then feeding both amplitude and phase (stored in two channels) into a CNN network to eliminate twin-image and self-interference-related artifacts. We can also find similar operations in other holographic reconstruction studies [25,63,72]. As for one-step reconstruction, the DNNs usually learn a direct mapping between the raw measurements and the final reconstructions in an end-to-end way without preliminary autofocusing or reconstruction steps. In the pioneer works, Wang *et al.* [20] and Ren *et al.* [73] use the in-line and off-axis DHM setups, respectively, to explore the capability of CNN-based networks in one-step holographic reconstruction for both amplitude and phase objects without knowing any prior information of the imaging process, and achieve promising results. Many of the reconstruction works fall into this category [32,34,43,65,74,75].

After pioneering implementations of deep learning in general holographic reconstruction, studies with different emphases have emerged. Dissatisfied with the unrealistic scenario setups where DNNs only deal with in-focus objects, researchers then take a further step using DNNs to address severe quality degradation in recovering out-of-focus samples [63,72]. Wu *et al.* [63] successfully apply a Res-UNet to extend the system depth of field (DOF) for reconstructed images with autofocusing and phase recovery performed at the same time. Zhang *et al.* [72] also train a modified U-Net on generated off-axis DHM datasets under different degrees of defocus and then test on both simulated and real data. The trained model can directly recover the phase from the defocused holograms within a certain diffraction range.

As the DNNs in previous works are all trained to recover either phase or amplitude in the separate learning process, Wang *et al.* [75] develop a one-to-two architecture (Y-Net), implemented by adding a second expanding path to the original U-Net. It can perform both intensity and phase reconstruction from one single hologram simultaneously. Another work from the group then further extends the simultaneous reconstruction to dual-wavelength DH for

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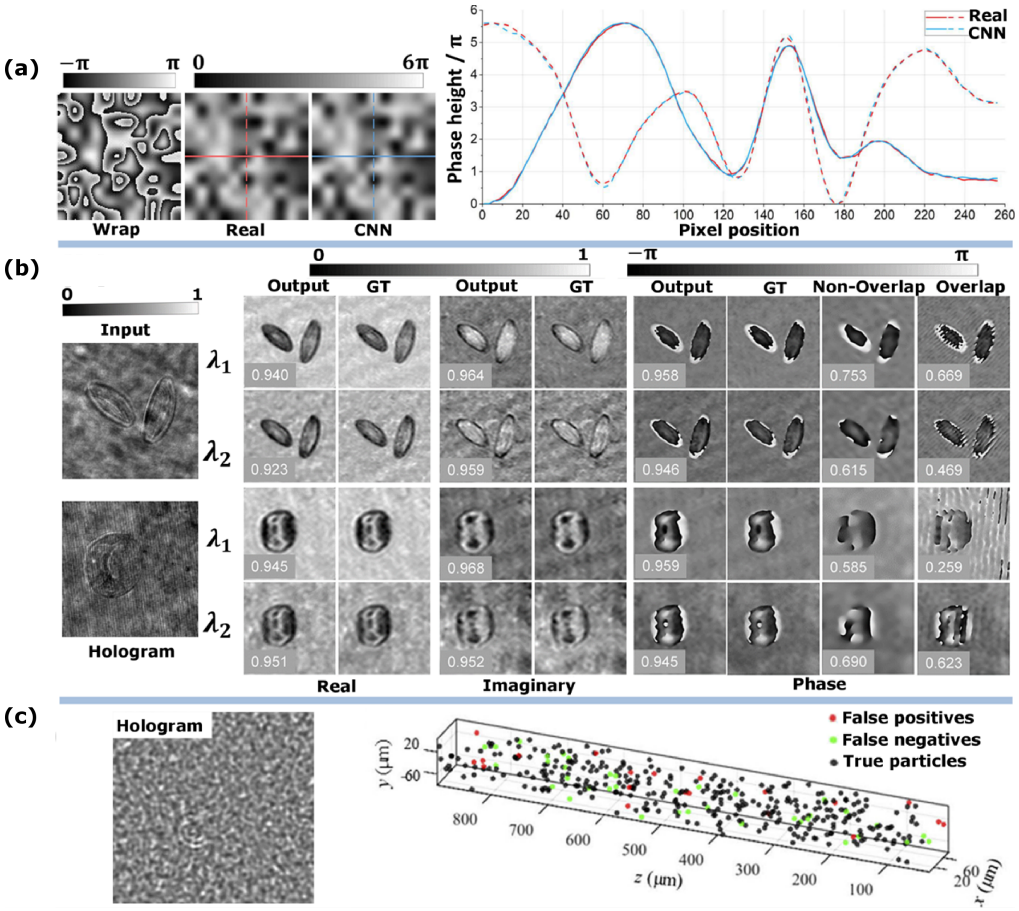

Fig. 3. Example results of learning-based reconstruction in DH. (a) CNN-based phase unwrapping with comparison plot of phase height between real and unwrapped phase (Adapted with permission from [64] ©The Optical Society). (b) Reconstruction results of complex amplitude and phase for one-shot dual-wavelength DH using Y4-Net with SSIM values presented on the corners (Adapted with permission from [65] ©The Optical Society). The last two columns are traditional reconstructions for non-overlap and overlap cases. (c) Example of 3D particle field reconstruction using U-Net (Adapted with permission from [66] ©The Optical Society).

resolving spectral overlap in phase recovery [65], where a total of four reconstructions, intensity and phase of two wavelengths, can be obtained at the same time (see Fig. 3(b)).

Many issues created by coherent holographic imaging, such as non-diminishing ripples, overlapped interference fringes, and coherent artifacts, can only be partially alleviated by reconstruction algorithms. Wu *et al.* [25] therefore propose a solution to use cross-modality image transformation to fuse the advantages of both coherent holographic microscopies and incoherent bright-field ones using a standard GAN framework.

Despite the predominance of CNNs in holographic reconstruction, there are several attempts to perform reconstruction with other promising yet less commonly used networks such as capsule networks and RNNs. Specifically, compared with CNN-based frameworks, a lightweight capsule-based network has been applied in intensity reconstruction from off-axis holograms with

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much fewer network parameters needed for comparable reconstruction quality [34]. Then in [32], a convolutional RNN has been demonstrated to present superior performance in reconstruction speed, quality, and DOF during phase recovery of in-line DHM.

For 3D holographic reconstruction, only a few learning results have been reported [37,66,76,77], mainly due to the difficulty in acquiring enough training pairs. Shao *et al.* [66] apply a modified U-Net for particle localization and use scanning microscopy to obtain ground truths (see Fig. 3(c)). In [37], Chen *et al.* implement unrolled networks to reconstruct particle size and location at the same time, which have also demonstrated that incorporating physical models can help reduce the quantity of data needed for sufficient training.

3.3. Image Enhancement: Super-resolution and Noise Suppression

As details smaller than the pixel size on the sensor chip are lost in DH recording according to the Nyquist-Shannon sampling theorem, the finite pixel size limits the spatial resolution of holograms [80]. Super-resolution techniques thus have emerged to extract high-resolution details. Conventional methods either rely on multi-frame measurements with time-consuming iterative computations [81] or sparsity-based algorithms, which require samples to be sparse [7]. These restrictions imposed on image acquisition, computational speed, and sample characteristics limit the applicability of DH in many areas.

Deep learning studies in holographic super-resolution usually construct an end-to-end mapping between images with low resolution (LR) and high resolution (HR). In [82], super-resolution CNN (SRCNN), initially proposed for focused images, has been retrained on the defocused holograms from in-line DHM and produced upsampled holograms with a large field of view and high-quality diffraction patterns. The ground truth HR holograms were generated by pre-trained SRCNN from focused LR holograms. GANs then start to stand out in super-resolution, ensuring sharper and realistic HR natural images. Liu *et al.* [83] demonstrate the performance of U-Net architecture under a GAN structure in super-resolving both pixel-limited and diffraction-limited in-line holograms of lung tissue sections and smear samples. They obtain ground truths by applying sub-pixel shift on multi-frame LR holograms recorded at different lateral coordinates. Luo *et al.* [78] then proposed a super-resolution method based on U-Net for lens-free in-line DHM. It uses the holograms as HR ground truths while digitally synthesizing LR holograms through a degradation operation mimicking the LR imaging process, which is shifting and downsampling the HR holograms (see Fig. 4(a)). They claim that training on datasets synthesized from raw measurements can still achieve robust performance on various types of samples, and thus can enable applications where HR ground truths are not available. Similarly, studies have also investigated the effectiveness of deep residual CNNs on super-resolving off-axis holograms with raw holograms as ground truth HR images and images downsampled using the bicubic interpolation method as LR holograms [84,85].

Most of these methods only perform a comparison with conventional super-resolution methods like bi-cubic, bilinear, and nearest neighbor, while only a few works [85] compare with other deep learning networks. Although still in a nascent stage, these studies demonstrate that deep learning approaches can achieve robust single image super-resolution in a non-iterative fashion, significantly accelerating data acquisition and reconstruction of HR holograms.

In addition to super-resolution, there are also studies performing holographic image enhancement with denoising networks. It could be very challenging to obtain high-quality images, as unwanted interference of coherent light would generate speckles observed as high-contrast, fine-scale granular patterns. Such noise severely degrades the observed image [86]. The signal-dependent nature makes it hard to suppress using common denoising methods like low-pass filters. Conventional solutions include experimental approaches and numerical algorithms. The former usually involve additional hologram capturing [87] or light source coherence reduction [88], imposing more rigorous requirements on experiments. The latter leverage prior knowledge

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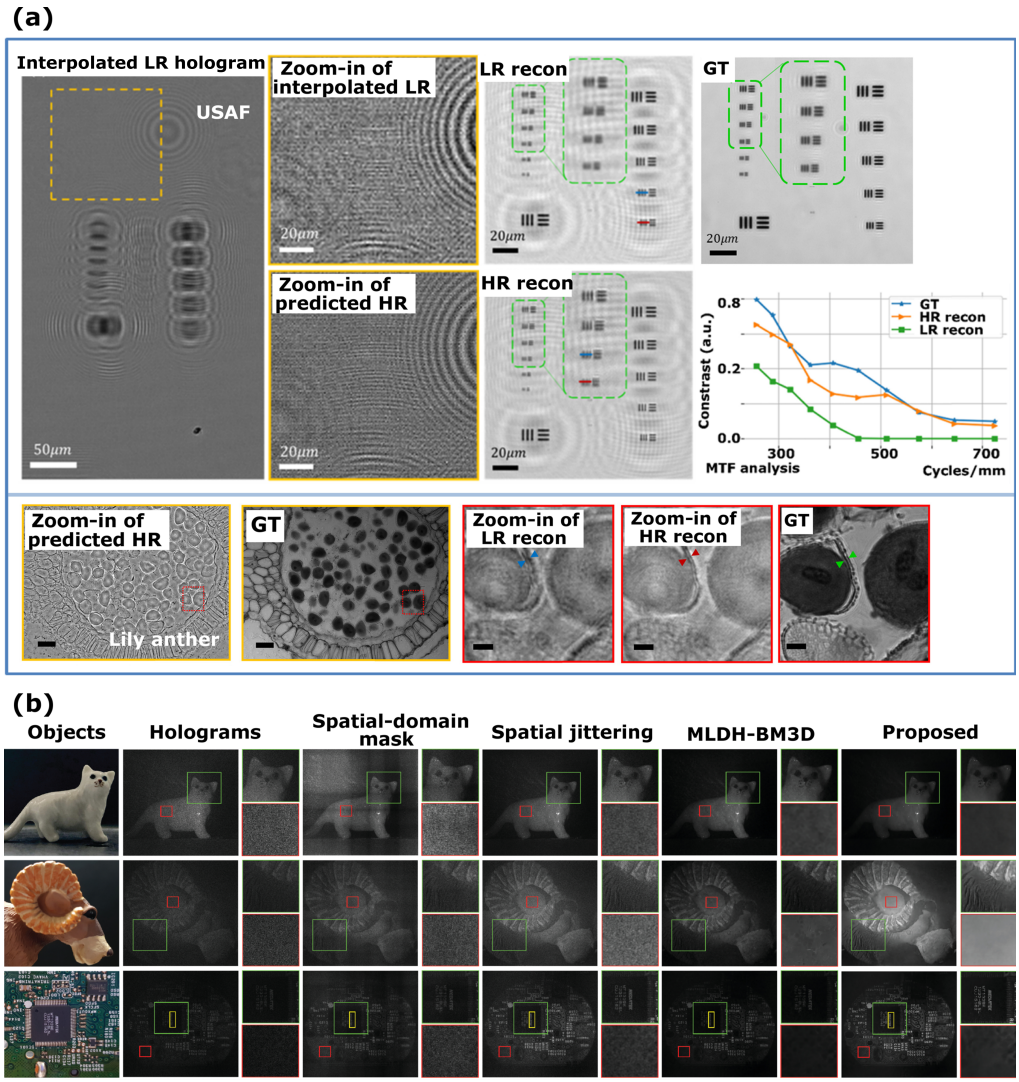

Fig. 4. Deep learning overcomes physical limitation in spatial resolution and enables reduction of coherent noise for DH. (a) Example of holographic pixel super resolution of different samples, where HR predictions of high image contrast calculated by modulation transfer function (MTF) are generated (Adapted with permission from [78] ©The Optical Society). (b) Speckle reduction for DH images using learning-based method and classical despeckling approaches (Adapted with permission from [79] ©The Optical Society).

or assumptions on the statistical characteristics of the noise [89], which show limited denoising performance and also restrict application areas.

In recent years, a growing number of studies have reported remarkable results in noise reduction using deep learning algorithms [79,90–95]. In particular, residual learning has been demonstrated to be very effective in various denoising tasks, including suppressing coherent noise in DH [79,91,92]. Jeon *et al.* [79] trained a residual U-Net on synthetic datasets with various

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levels of speckles and then tested on real intensity images, which outperformed state-of-the-art conventional methods, including spatial-domain mask, spatial jittering, and MLDH-BM3D (see Fig. 4(b)). Park *et al.* [92] applied a denoise convolutional neural network (DnCNN) to get despeckled orthographic amplitude views before generating speckle-free reconstructions.

Some studies then proposed deep learning solutions for data challenges encountered in speckle suppression, such as training with unpaired datasets [93], or no clean targets as ground truths [94], via cycle-consistent networks. Instead of taking DNNs as a black box, researchers have tried to incorporate prior knowledge with denoising networks. Chen *et al.* [95] applied wavResNet, initially proposed for CT images, to amplitude specimens in lensless in-line DHM. When training in the wavelet domain, noise presents simpler topologies than in the spatial domain, facilitating faster learning.

3.4. Object Detection and Classification

DH can be used to coherently image small objects with high resolution up to micro- and nanometer scale. Therefore, it is often used to detect and analyze such objects as cells, microorganisms, particulate matter in the air, tiny deformation on mechanical parts, etc. Recently, with the help of deep learning, the performances of DH on image processing steps, processing time, and detection accuracy are significantly improved.

Cell identification and disease diagnosis. The identifications of biological cells and disease diagnosis are one of the earliest and most prominent application areas of DL. In 2017, Yi *et al.* [10] use two fully convolutional neural network (FCN) models to extract red blood cells (RBCs) from the holographic images, which are captured by an off-axis DHM with a modified Mach-Zehnder structure. Assisted by the FCN, the RBCs can be automatically extracted from their phase images. However, manual segmentation of the phase images and the dataset labeling are still needed to complete the cell extraction. In the same year, Jo *et al.* [96] use CNN to classify the holographic images of Bacillus anthracis spores. Different from Yi *et al.* [10], the network is trained on the label-free living cells without manual feature extractions. The network has the capability to automatically extract the key traits encoded in the biological holograms. With the experimental demonstrations, this DL-based method shows outstanding performances in classification accuracy, which outperforms other previous techniques.

Later, in 2018, transfer learning is combined with DH and applied in molecular diagnosis [39–41] to reduce the complexity of sample processing and image collections of some living cells (see Fig. 5(a)). Common attempts are to use networks pretrained on natural images where a large number of labeled data are available, such as ImageNet, and then fine-tune the models with limited data from the target scenario [38]. In particular, Kim *et al.* [39] fine-tuned a pretrained VGG19 network to classify the raw lens-free digital in-line holographic images of cancer cells without reconstruction. Assisted by transfer learning, the experimental results show a robust classification performance and have the potential to be used in portable point-of-care diagnostics. In 2019, Rubin *et al.* [41] proposed a method to classify the stain-free quantitative phase maps of healthy cells and the cancer cells captured by an off-axis digital holographic system with the combination of transfer learning and GAN.

In recent years, more advanced deep learning networks have also been applied to some portable digital holographic devices. O'Connor *et al.* [31] demonstrate a bi-directional long short-term memory (Bi-LSTM) network to deal with the video-rate data of live red blood cells recorded by a 3D-printed shearing DHM. Their method can not only classify the cow and horse red blood cells with similarity in morphology (see Fig. 5(b)), but also extract features from time-varying images for behavior analysis of the cells. O'Connor *et al.* [97] later successfully apply a similar method to classify the healthy and COVID-19 positive red blood cells and complete the rapid screening of COVID-19.

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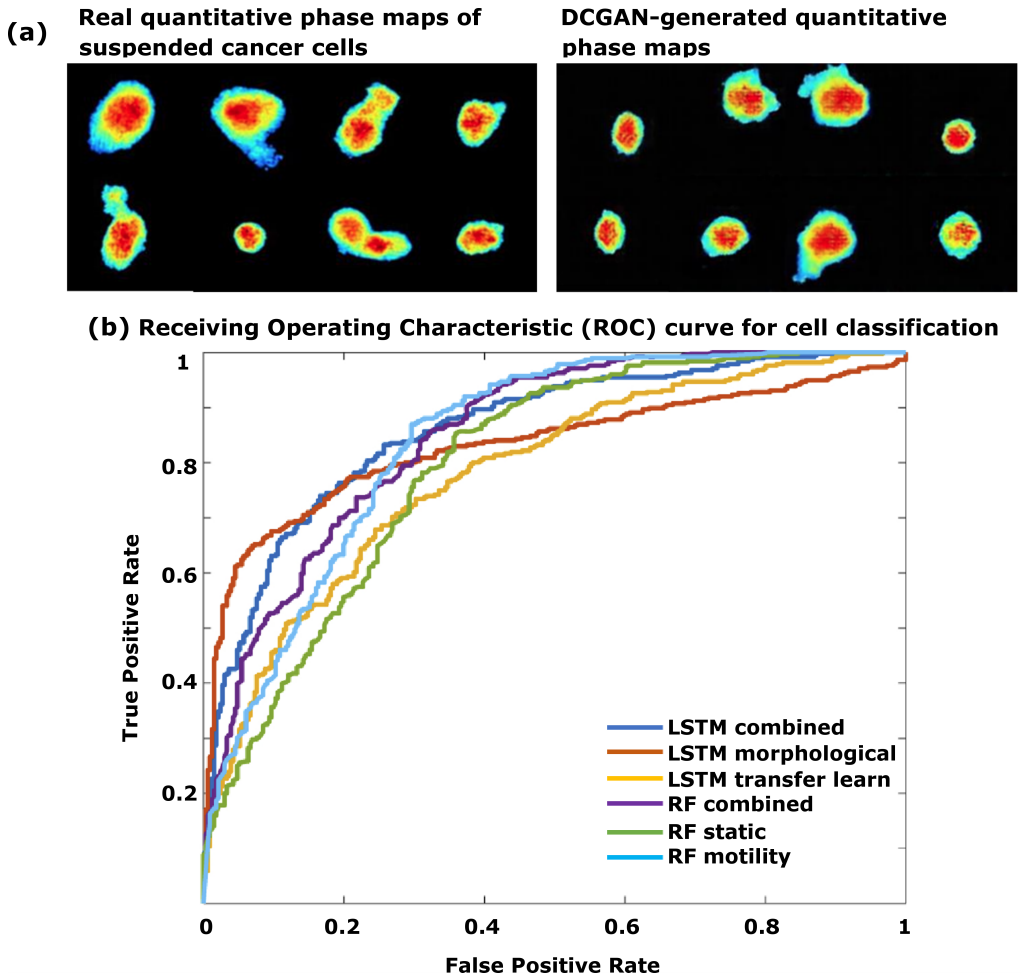

Fig. 5. Deep learning for cell identification and disease diagnosis. (a) Deep learning is used to generate the phase images of cancer cells for further cell classification (Adapted with permission from [40]). (b) Deep learning is used for the classification of cow and horse red blood cells. The classification performance is demonstrated in terms of receiving operating characteristic curve (Adapted with permission from [31] ©The Optical Society).

Live bacteria and virus detection. Live bacteria and microorganisms are usually tiny, transparent, or semi-transparent phase objects with time-varying mobility. Digital holographic or the quantitative phase imaging (QPI) system is a powerful and high-resolution imaging method for such objects. However, imaging and detection require sample dyeing and manual counting with low efficiency and accuracy. Deep learning has been demonstrated to improve both processing speed and performance. Especially, Zhang *et al.* [11] show a learning-based digital holographic imaging platform to rapidly detect the motile parasites without the requirement of manual image labeling. By using a CNN network to analyze the time-lapse holographic motile microorganisms' speckle patterns, this platform can complete a sensitive detection of trypanosomes in a high-throughput optically dense bodily fluid. With the advantages of being portable and time-saving, it could be further used for other sensitive parasitic infections. Similar

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studies are being conducted on the detection of the herpes simplex virus (HSV). Wu *et al.* [98] propose a deep learning-based holographic image reconstruction method to rapidly image and quantify the tiny particles in 3D. They successfully apply it in the 3D detection of HSV with high throughput. Researchers have also made breakthroughs in the classification of live bacteria and their time-lapse activities. For example, Wang *et al.* [12] demonstrate a deep learning-based method for periodically recording the holograms of live coliform bacteria and classifying the corresponding species. Getting rid of the limitations of the sample volumes and complexities, this method can complete rapid and automatic analysis and classification, which provides a powerful tool for bacteria detection.

Environmental quality control and pollution monitoring. Pollutants in the air are generally on the micro- or nano-meter scale and are mostly caused by vehicle exhaust emissions, industrial emissions, or the incomplete combustion of fossil fuels. This kind of pollutant is difficult to be identified by the naked eye, easy to be inhaled into the body, and can cause non-negligible damages [99]. Therefore, a fast and accurate automatic detection system is needed to monitor them in real-time. Kim *et al.* [100] accomplished the detection of particulate matter (PM) by analyzing the holographic speckle pattern and using an autoencoder and regression network called Holo-SpeckleNet for automatic classification. The speckle pattern datasets of PMs are captured by a digital in-line holographic microscopy system. The experimental results show that this method could detect PM with a concentration over the air quality index of 150, which is an unhealthy level for humans. This method is expected to be further applied on a compact air quality monitoring device.

In addition, the detection of microplastic particles becomes a hot topic in recent years. Microplastics refer to plastic particles with a diameter smaller than 5mm, mainly from the inadequate decomposition of large plastic waste and industrial emissions. They can be ingested by marine organisms or humans, impairing digestive systems and even endangering life. Since COVID-19, the widespread use of disposable masks, medical syringes, and disposable tableware has exacerbated the level of microplastic particle pollution, making it an urgent problem to be solved. At present, the main detection methods include Fourier-transform infrared spectroscopy (FTIR), Raman spectroscopy, visual inspection, and so on. These methods not only demand sample filtration, dyeing, tablet loading, and other pre-processing but also require manual comparison and detection. These time-consuming processes and professional-level requirements of the tester hinder automatic and rapid detection. Thus, deep learning methods have been used to fill this gap. Zhu *et al.* [101] propose an automatic digital in-line holographic system to detect and classify the microplastic particles with other dust particles in the natural environment. The specially designed network can extract the features of the holographic image. The experimental results show that this lightweight network consumes less computational resources and is suitable for portable detection devices without a graphics processing unit or a large computing unit. In addition, they have also open-sourced a fully labeled microplastic particle holographic dataset for network training, filling a gap where no relatively complete holographic dataset has been publicly available before. Considering that the holographic dataset usually has a small size and the distribution of various classes is imbalanced, they also proposed a method based on transfer learning to effectively improve the accuracy of classification and detection [42]. This method is also attractive for *in situ* microplastic detection applications, such as underwater microplastic pollutant monitoring.

3.5. Three-dimensional Particle Tracking

As mentioned earlier, DH encodes the three-dimensional (3D) spatial information of the object and is, therefore, suitable for 3D reconstruction and tracking of the object. Similar to previous applications, deep learning eliminates manual image processing steps and automatically completes the 3D tracking of objects, which greatly improves the working efficiency. For example, Lee

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et al. [102] propose a deep learning-based digital holographic system for accurate and rapid 3D microparticles tracking, which can precisely determine the position information of the microparticles in a circular microtube using a well-trained CNN. Chen *et al.* [37] also design a model-based holographic network for 3D particle holographic image tracking. It is worth noting that this method can reduce the influence from defocus noise and twin-image entanglement of the digital in-line holographic system. By using the free-space point spread function as a physical prior to guiding the network training, they obtained a good performance of 3D particle localization and reconstruction. Compared with CNN, this kind of advanced and developed network provides more power for DH.

In addition, deep learning also facilitates the link and conversion between the digital holographic system and other microscopic systems, such as bright field microscopy. Wu *et al.* [25] demonstrate a GAN-based network that can be used to transfer the holographic image into a bright field microscopic image. This network relies on data-driven network training to reproduce the bright field microscopic images without speckles and artifacts based only on a 2D holographic snapshot. The results of 3D reconstruction experiments of bioaerosols confirm that this method can not only excavate the spatial encoding ability of DH but also make good use of the artifact-free imaging characteristics of bright field microscopic imaging technology, which provides a new idea for the improvement of optical imaging technology.

3.6. Image Understanding, Holographic Display and Compression

Digital hologram only records the spatial coherent information of the object without surface color information. Compared with digital images and other true-color images, it loses part of the color characteristics of the sample. To compensate for this, researchers used deep learning to intelligently stain and reconstruct the holograms. Riverson *et al.* [103] develop a digital staining technology called PhaseStain, which can virtually stain the QPI images by training the network on corresponding bright field microscopy images. They successfully apply this technique to the holographic images of human skin, liver tissue, and kidney, which are captured by an in-line lensfree holographic system. This method eliminates the need for manual staining of samples and has high efficiency.

Deep learning has also been successfully applied in computer-generated holography (CGH) [104–107], which generates the customized optical field by modulating the coherent light beam using holographic display devices such as the spatial light modulator. To ease the computational burden associated with the traditional iterative methods, Horisaki *et al.* [104] apply CNNs in estimating the complex field at a certain propagating distance in a single feed-forward inference process. Eybposh *et al.* [105] then develop an unsupervised model to relax the requirement of explicit ground truth labels. Based on the camera-in-the-loop [44] optimization procedure, the holographic near-eye display with automatic calibration is further improved with novel holographic display hardware architectures [106] and physics-based models by combining angular spectrum method and CNNs [107].

In addition, due to the large amount of feature information contained in holographic images, some high-frequency features will be missing during image compression, storage, and reconstruction. If the traditional JPEG standard is used to compress the hologram, the decompressed image quality will be greatly damaged. Considering this, Jiao *et al.* [108] propose a "JPEG + deep learning" hologram compression scheme, which can greatly reduce the artifacts caused by the lossy compression, and successfully apply to the compression of computer-generated phase-only holograms.

4. Outlook

Despite the remarkable initial progress of deep learning in a wide range of DH-related applications summarized above, the specific DNNs and learning techniques used in most DH studies noticeably

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lag behind the latest advancements. The majority of the image classification studies in DH use classical CNNs such as VGG networks and ResNets. In holographic reconstruction tasks, the amplitude or phase recovery mainly uses U-Net. Some emerging deep learning models or techniques, such as transformer and attention mechanism [16], with remarkable improvements in many other measurements, have not been thoroughly studied in DH. For example, attention mechanisms that can capture non-local correlations within holograms are likely to help solve different DH problems. In addition, most DH studies use standard supervised learning, of which the performance is heavily relying on the quality of the datasets. Very few attempts have been made on techniques reducing such dependence. Moreover, DH is an active research area covering a vast array of topics [109], and many of them remain open problems for learning-based algorithms. Hence, the full potential of deep learning in DH applications remains under-exploited, requiring more research efforts in various fields. We summarize several potential directions that are worth further exploration in the following.

Open source benchmark datasets. Currently, there are hardly any large holographic datasets, such as [110–112], in the research community. It restricts the use of DNNs, makes the comparison between deep learning methods very difficult, and raises research barriers in DH. In addition to the quantity, unbiased datasets with balanced distribution are more scarce, especially for biomedical applications, which increases the difficulty of avoiding hallucinations and erroneous predictions. Thus, large and representative benchmark datasets should receive more attention.

Multi-modality. Deep learning provides great potential for integrating multi-modal and multi-dimensional data. For example, image fusion technology [113] can be used to combine images collected by different types of optical systems, such as fluorescence and magnetic resonance imaging (MRI), to display multiple types of object features simultaneously in one image. By fusing the holographic fringe patterns of biological cells with MRI and fluorescence information, the generated samples can be used to obtain the cell surface structure, internal spatial structure, and material composition information. Regarding some 3D objects or moving objects, one can use deep learning to predict the motion trajectory based on one single hologram [114]. Traditional DH requires the manual acquisition of several holographic images at different positions to reproduce the motion of dynamic objects. The use of dynamic generation technology can enable the automatic generation of 3D space trajectory information, eliminate the requirement of multiple imaging and improve imaging efficiency.

Cross-domain analysis. It is often the case that the conditions of holographic acquisitions for training and testing data vary since the limited number of holograms leveraged in training cannot cover all circumstances of real-world scenarios. As a result, models trained on source domains may lead to poor predictions on unseen holograms with different statistics from the target domain. To this end, it is necessary to study common knowledge or features across diverse DH instruments and experimental environments. Thus, domain adaptation (with a small number of samples from the target domain) or even domain generalization (with no sample from the target domain) is of great interest [115]. A possible direction is to use the deep learning generation technology to simulate the imaging effect under different light sources and automatically switch the scene under different imaging environments. For example, one can use holographic images captured by a laser source to simulate those generated using white light or under a low illumination condition.

Employing physical knowledge. Current studies generally lack a deep understanding of how to leverage the specific characteristics of DH when building a network. Most of them employ a DNN as a black box that learns a mapping between inputs and labels without any prior knowledge. Such is beneficial to circumstances where the acquisition of analytical models is difficult or infeasible. However, the established physical knowledge of holographic systems is often attainable and informative, and thus can help resolve inverse imaging problems. The unrolled network for holographic 3D particle imaging [37] and the untrained model used in phase imaging [55] are successful initial attempts. Yet, little understanding of the underlying

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mechanisms has been offered, particularly for untrained models, which can generate surprising results without training beforehand. As for unrolled networks, the nature of its customized structure brings in challenging training schemes for complex optical geometries in DH, which requires further investigation. Systematic studies that compare different selections of unrolling algorithms and choice of fixed and trainable parameters are also lacking. Further study on the standardization of these networks is thus needed. Moreover, incorporating physics in learning often brings in model mismatch problems due to imperfect priors, which impairs the robustness of these approaches [116]. How to address this issue is critical for translating model-based networks to broader DH applications.

Joint design of software and hardware. As most DH applications use deep learning for post-processing, the performance is strictly bounded by the quality of captured images. Thus, the joint optimization of experimental setups and learning-based reconstruction algorithms would be a promising future direction to break the current limitations. For example, the camera-in-the-loop [44] proposed for computer-generated holography provides a good demonstration, where the wave propagation, as well as some optical parameters, can be learned according to a specific display application. There are also several emerging studies using deep learning to optimize imaging parameters and physical systems, such as designing illumination patterns in QPI systems [117], optimizing point spread functions, illumination power, and focus positions in single-molecule localization microscopy [118].

Storage, compression and transmission. For the storage and transmission of holographic images with rich features, deep learning can be used to reduce the quantity of feature information retained during image compression and the size of the image after compression [119]. Currently, deep learning methods for compression are mainly lossy. They are generally universal and lacking in specificity for holographic images. In addition, the evaluation metrics for compression performance are mostly based on human vision, such as PSNR, SSIM, etc. Whether this kind of image quality evaluation metrics can accurately reflect the performance of holographic image compression needs further discussion.

Biomedical imaging and analysis. Deep learning has been widely used for the detection and classification of cells in DH with promising results. However, the implementations of DNNs in many other biomedical applications of DH remain unexplored. They include the determination of biological characteristics of cells, such as the refractive index, and observation of the changes within the cell, such as the transportation of intracellular substances, immune behavior, and the judgment of division cycles. Moreover, using DH to assist in analyzing the effects of drugs on cancer cells is one of the current research hot spots [120]. How deep learning can help in related studies is also an exciting future direction.

Information encryption and security. The DH-based optical image encryption technology has the advantages of large capacity and high confidentiality. By angle and wavelength multiplexing, it can encrypt the image information. Currently, the encryption and decryption mainly use the optical characteristics of DH, such as Fourier and Fresnel transform. In the future, it is interesting to investigate related researches using deep learning techniques.

5. Conclusion

In summary, the application of deep learning algorithms opens up new opportunities for studies in DH and spans an increasingly wider range of tasks. There still remains a great number of exciting topics and research problems waiting to be explored. With the effort of this article, we hope to stimulate more joint initiatives of experts in deep learning and holography to work collaboratively and add momentum to the future continuous study in this fast-developing field.

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