

Redefining frontiers of computational imaging with deep learning

Tianting Zhong,^{a,†} Haofan Huang,^{a,†} Haoran Li,^{a,†} YongKeun Park,^{b,*} and Puxiang Lai^{a,c,d,*}

^aDepartment of Biomedical Engineering, The Hong Kong Polytechnic University, Hong Kong, China

^bDepartment of Physics, Korea Advanced Institute of Science and Technology, Daejeon, Republic of Korea

^cShenzhen Research Institute, The Hong Kong Polytechnic University, Shenzhen, China

^dPhotonics Research Institute, The Hong Kong Polytechnic University, Hong Kong, China

In recent years, the integration of deep learning with computational imaging has fundamentally transformed optical imaging paradigms. Traditional methods encounter significant challenges when reconstructing high-dimensional information in complex scenarios^[1]. By leveraging the powerful nonlinear modeling and advanced feature extraction capabilities of deep learning, these barriers have been effectively overcome, enabling end-to-end optimization—from optical system design to image reconstruction^[2]. This shift transforms optoelectronic imaging from a conventional “what you see is what you get” model toward a more adaptive “what you see is what you need” approach, catalyzing breakthroughs across diverse applications including optical imaging, medical diagnostics, remote sensing, and beyond.

In a seminal review recently published in *Photonics Insights*^[3], Luo *et al.* systematically outlined the pivotal role of deep learning and its latest advancements within computational imaging. Figure 1 provides a schematic overview of the key concepts of the review. Their comprehensive analysis highlights how deep learning methodologies are redefining imaging technology across three transformative domains: computational optical system design, high-dimensional light-field decoding, and advanced image processing and enhancement.

1 Redefining Optical System Design

Traditional optical design, usually reliant on iterative empirical optimization, suffers from inefficiency and complexity. Deep-learning-driven approaches span wavefront sensing, aberration compensation, lens-free imaging, correlated imaging, and photon-counting imaging. These approaches utilize exceptional nonlinear modeling and problem-solving capabilities of deep learning to enhance the efficiency and precision of optical system design, while also democratizing access to advanced photonic architectures. This paradigm shift exemplifies how data-driven intelligence is redefining the boundaries of optical

engineering^[4], bridging the gap between theoretical innovation and practical implementation.

2 Decoding High-Dimensional Light Fields

The analysis of high-dimensional information of light fields expands the capabilities of imaging systems in terms of penetration, resolution, and data dimensionality. Deep learning empowers imaging systems to transcend traditional two-dimensional (2D) intensity capture. Compared with traditional 2D intensity imaging, computational imaging based on deep learning can analyze complex target information obscured by scattering media and visualize previously unobservable targets. In terms of resolution improvement, deep learning improves the quality of reconstructed images and optimizes processing efficiency. In addition, computational imaging integrated with deep learning can simultaneously capture multimodal data streams, including spectral and polarization information. This multimodal information fusion makes advanced visual tasks such as target detection, semantic segmentation, and three-dimensional reconstruction possible, effectively bridging the gap between physical hardware limitations and application demands.

3 Computational Processing: from Enhancement to Decision-Making

As the final link in the computational imaging chain, computational processing plays an increasingly pivotal role in enhancing imaging quality, improving perceptual capabilities, and supporting decision-making processes^[5]. Deep learning excels in image fusion (spanning digital photography, multimodal integration, and remote sensing scenarios), denoising (leveraging both supervised and unsupervised frameworks), and image enhancement (addressing low-light environments, underwater imaging, and medical diagnostics). Supervised and unsupervised frameworks have achieved robustness and efficiency in real-world scenarios and overcome the limitations of traditional imaging paradigms, setting new benchmarks for perceptual quality and diagnostic accuracy.

4 Challenges and Future Trajectories

Despite promising progress, several critical challenges persist. First, strong data dependency: domain gaps between simulated and real-world data severely limit model generalizability.

*Address all correspondence to YongKeun Park, yk.park@kaist.ac.kr; Puxiang Lai, puxiang.lai@polyu.edu.hk

[†]These authors contributed equally to this work.

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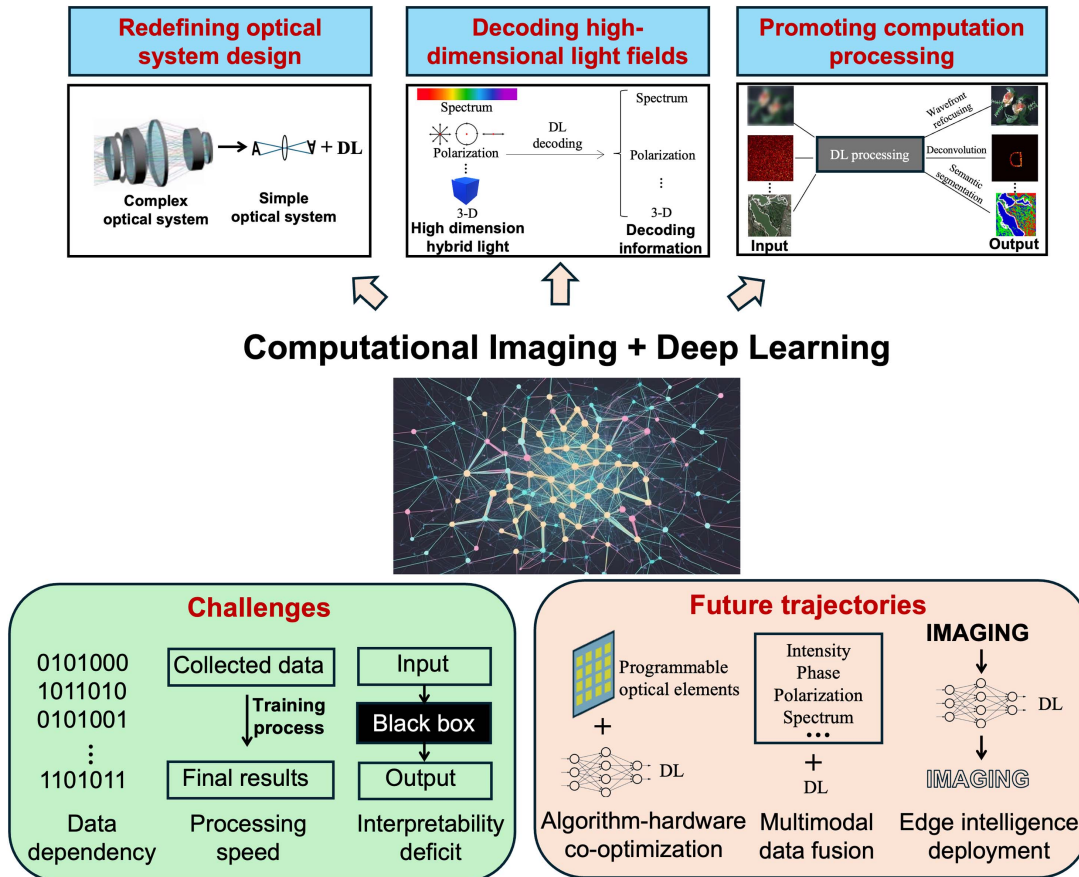


Fig. 1 Deep learning-driven computational imaging: impacts, challenges, and future trajectories.

Bridging these gaps will require embedding physical priors^[6] and employing cross-domain transfer learning^[7] approaches.

Moreover, achieving broad generalizability is essential. To ensure effective adoption of deep learning models across multiple organizations, it is crucial to reduce variations in protocols and equipment. Developing models robust to these variations or training models using commercially available standardized equipment can significantly enhance wider adoption and practical utility^[8,9].

Second, real-time processing presents significant bottlenecks. Complex network architectures often cannot meet the stringent requirements of millisecond-scale imaging. Therefore, developing lightweight architectures and adopting integrated hardware-software co-design approaches are essential to overcome these limitations.

Last, the interpretability deficit remains a critical issue. The black-box nature of many deep learning models restricts the understanding of underlying imaging mechanisms. Emerging techniques such as differentiable rendering^[10] and attention mechanisms^[11] offer promising pathways to enhance interpretability.

Looking ahead, the integration of computational imaging and deep learning is expected to evolve along three key trajectories. First, algorithm-hardware co-optimization^[12,13]: the joint design of programmable optical elements (e.g., metasurfaces) and neural networks will enable end-to-end “encoding-reconstruction” systems^[14]. Second, multimodal data fusion^[15]: the integration of multi-dimensional data (light field, polarization, spectral, etc.) will facilitate the development of universal imaging

frameworks. Last, edge intelligence deployment^[16]: lightweight models based on edge computing will drive widespread adoption of computational imaging on mobile IoT platforms.

In summary, Luo *et al.*’s review serves as a valuable resource, guiding newcomers and providing seasoned experts with insights to navigate this rapidly evolving field. As computational imaging and deep learning converge, they promise unprecedented capabilities ushering in an era where imaging systems adapt dynamically to human needs.

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