Deep Learning with Specialized Training for Fast Computer Generated Holography

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Abstract

We recently introduced a new algorithm for computer-generated holography based on unsupervised deep learning. The algorithm yields high fidelity holograms in a few milliseconds, outperforming alternate methods that require many iterations and longer computation times. Here, we demonstrate that substantial gains in performance can be obtained by training the CNN with custom datasets selected to be specific to a particular application. Simulation results validate our approach with up to 20% more accuracy in holograms

Algorithm & Performance

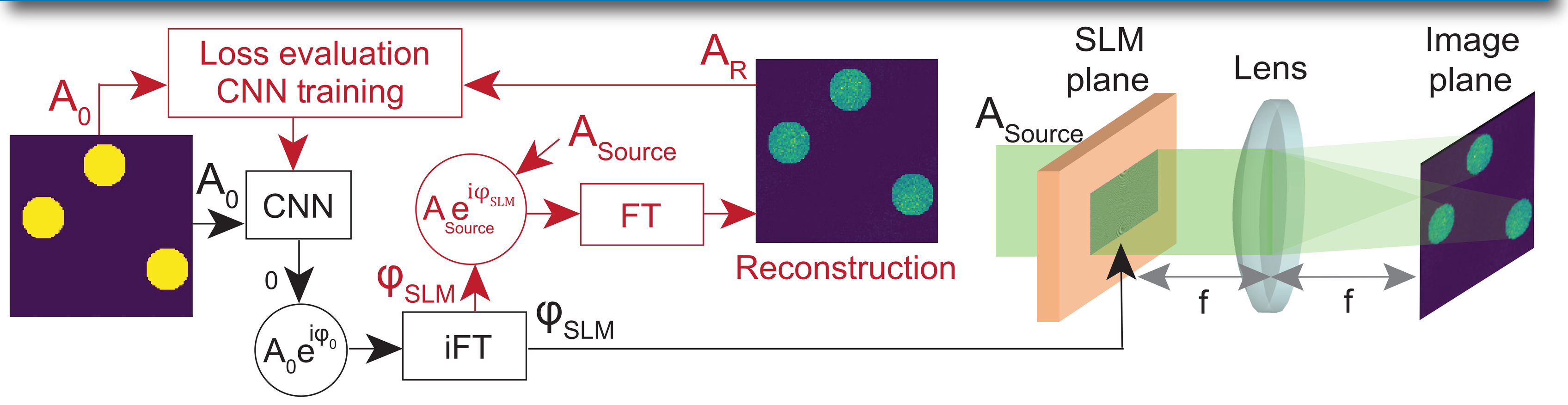
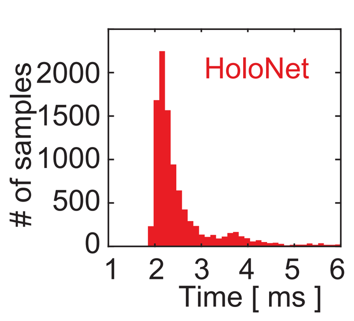


Figure 1: HoloNet during training (red) and operation (black)

HoloNet is a new deep learning structure that generates high fidelity holograms with unsupervised training. The computational framework is shown above. HoloNet relies on a U-Net CNN model to compute a complex field $Ae^{i\varphi_0}$ that best represents a feasible hologram matching a custom input amplitude A_0. In-place hologram computation preserves the spatial correspondence between input and output and best leverages the capabilities of the CNN in spatial feature processing. An inverse Fourier Transform (iFFT) simulates the reverse propagation of the optical field through the optical system and yields the solution for phase holography, φ_{SLM}. During training (in red), we simulate the hologram by forward propagation (FT) of the complex field, $A_{Source}e^{i\varphi SLM}$, where A_{Source} represents the ampltude of the coherent light source. Our goal is for the reconstruction to match the desired illumination amplitude, A_0, enabling unsupervised training of HoloNet.



$$\text{Accuracy} = \frac{\int A_0^2 A_R^2}{\sqrt{\int A_0^4 \int A_R^4}}$$

$$\text{Efficacy} = \frac{\int_{A_0>0} A_R^2}{\int A_R^2}$$

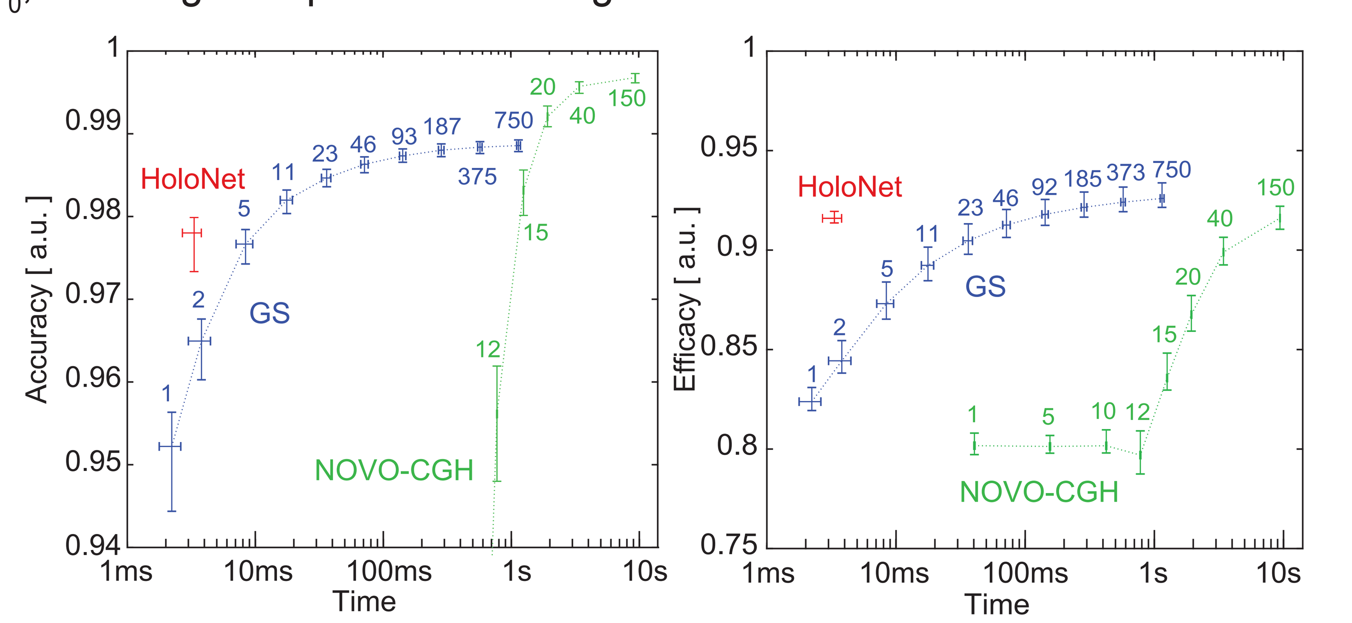


Figure 2 : HoloNet performance vs speed, in comparison with existing holography techniques

A popular approach for computing holograms relies on iterative projection algorithms such as Gerchberg-Saxton. This method is easy to implement and yields acceptable solutions after a few cycles, but offers no guarantees of quality or convergence. Conversely, optimization algorithms such as NOVO-CGH improve exploration and identify better solutions at the expense of longer computation time. Both methods require the end user to choose the number of iterations and prioritize either the computation speed or the hologram quality. Deep learning algorithms are perfectly suited to solve multidimensional nonlinear problems like CGH, and, with offline training, can eliminate trade-offs between speed and quality. HoloNet, in red, outperforms existing methods in speed and performance

References

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3. O. Ronneberger, P. Fishcer, and T. Brox, “U-net: Convolutional Networks for biomedical image segmentation,” in “International Conference on Medical image computing and computer-assisted intervention,” (2015), pp. 234-241.

Results

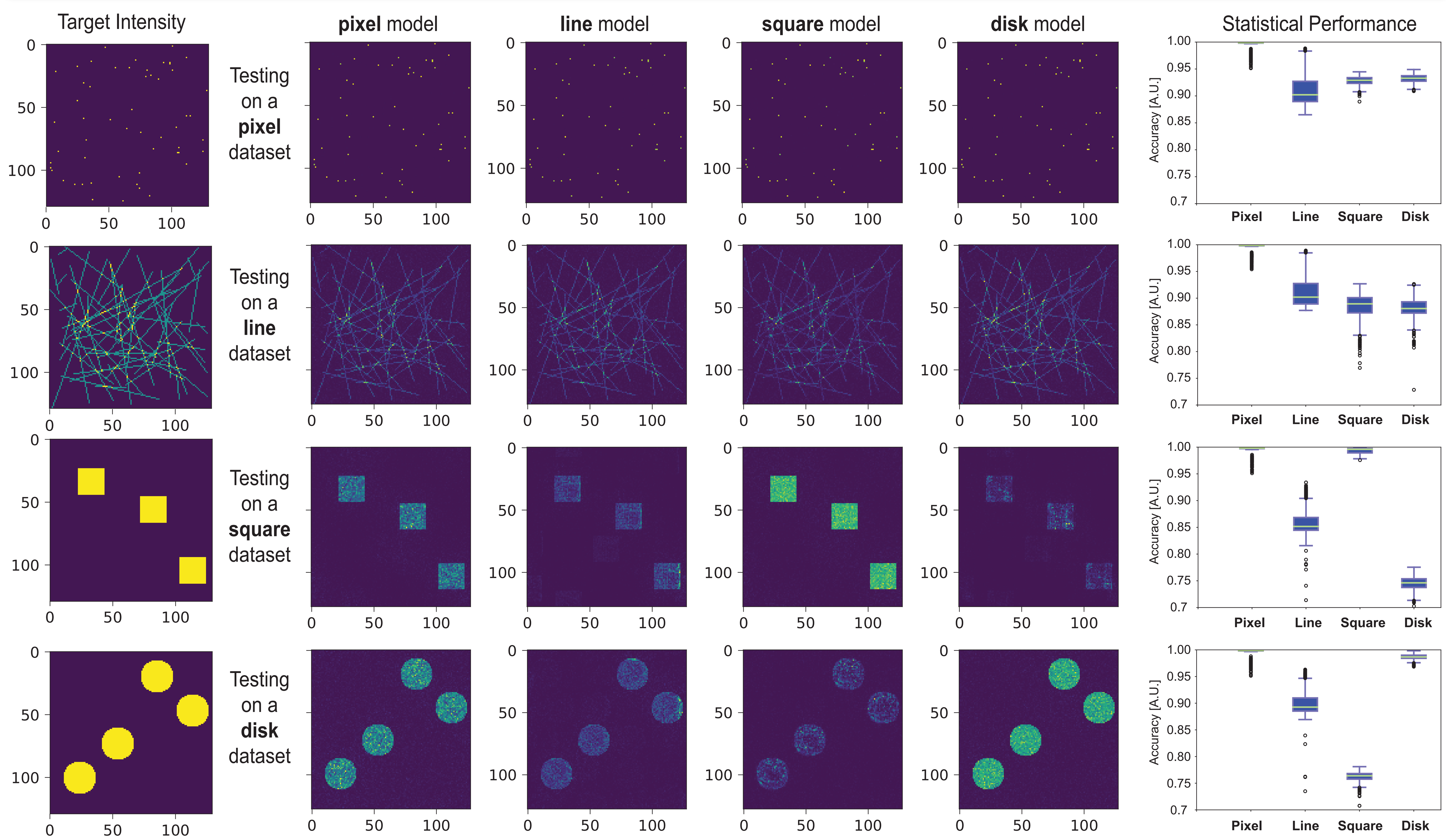

Figure 3 : HoloNet performance comparison after training and testing the model on four shape-specific datasets. Illustrations (left) and statistical accuracy data.

Our simulation results, indicate that HoloNet renders holograms with greater accuracy when the pattern selected for testing belongs to the same category of representative inputs for which the model was trained. Left, sample images show that Holonet attempts to fit shapes in targeted location regardless of the input data, indicating successful training. Right, statistical data for 1000 randomized testing samples evaluates the performance of the model for large populations. As shape complexity decreases, we observe that accuracy improves regardless of the training dataset, mitgating the need for specialized training.

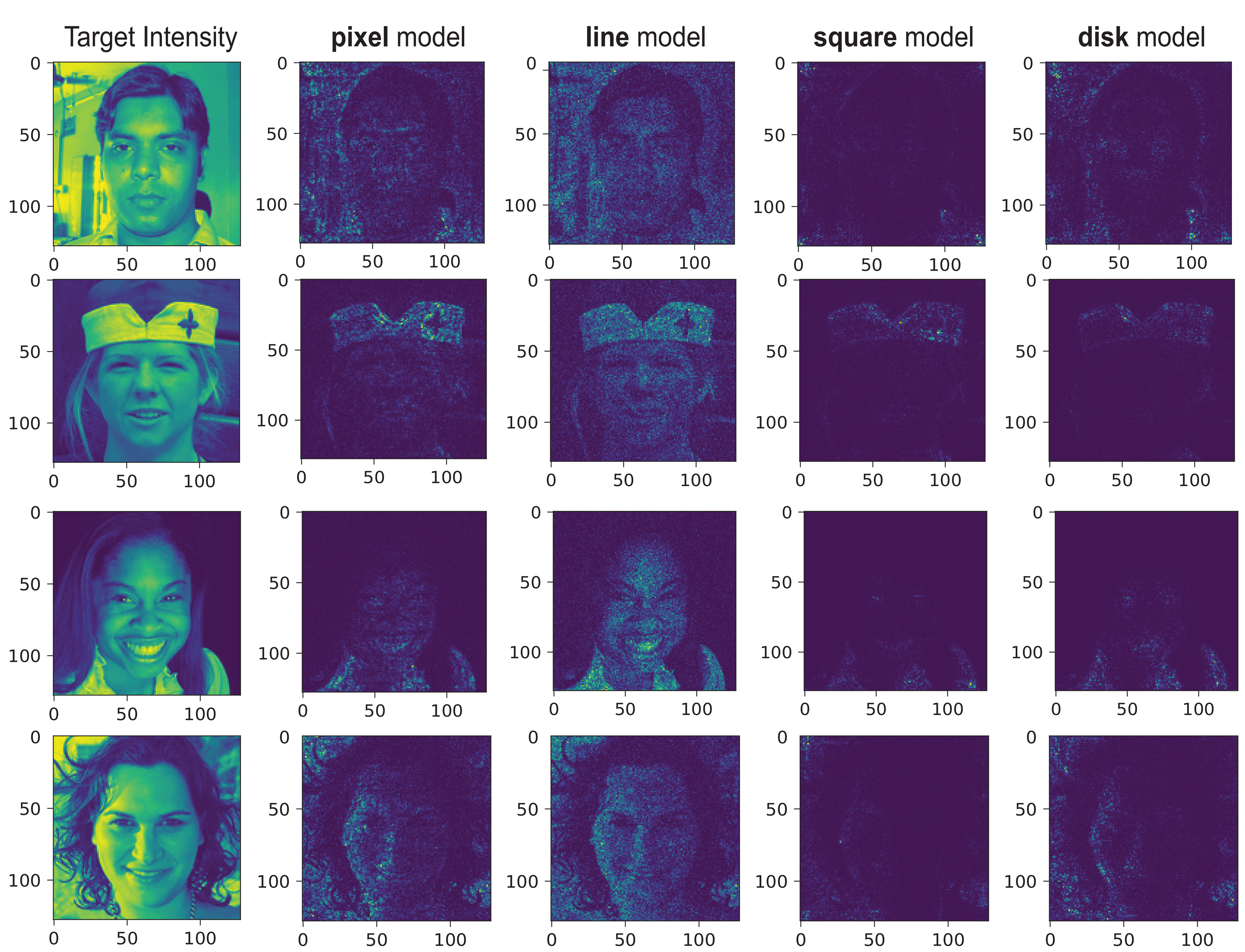

Figure 4 : HoloNet performance comparison after training and testing the model on facial images.

Data set : https://github.com/NVlabs/ffhq-dataset

Figure 4 shows how each version of HoloNet trained on varius shape subtypes (as in Figure 3) continues to imprint the shape for which it was trained when reconstructing the target image. The disk model attempts to reconstruct eyes to some extent while the square model is able to reconstruct the hat in the second image. The line and pixel model have the most success in reproducing the target image which is a result of the shapes being fundametal building blocks to create natural images. Both squares and disks are a combination of lines, while a line itself is a series of pixels. This gives both models a broader range of shapes they can reconstruct, improving their accuracy. **In conclusion,** while convolutional Nueral Networks are able to synthesize holograms at record speeds, but that fixed computational capabilities restrict performance. To address this issue, we proposed specialized training with datasets that mimick typical inputs. Simulation results show a definite gain in performance, at the expense of performance in rendering other patterns beyond the training data. The authors acknowledge financial support from the Burroughs Wellcome Fund (CASI Award), and from the NVIDIA GPU grant program.