Science

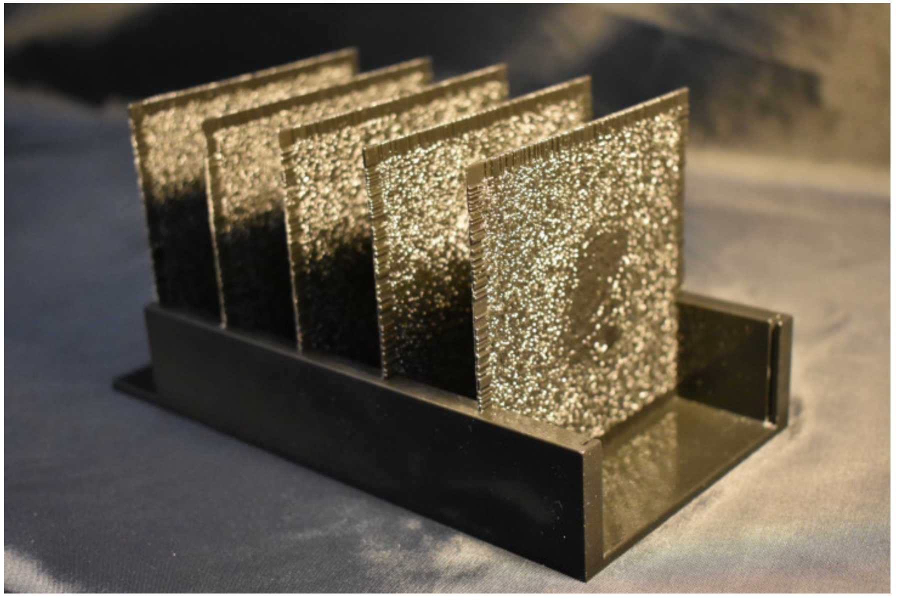
REPORTS

Cite as: X. Lin *et al.*, *Science*
10.1126/science.aat8084 (2018).

All-optical machine learning using diffractive deep neural networks

Xing Lin[1,2,3]*, Yair Rivenson[1,2,3]*, Nezih T. Yardimci[1,3], Muhammed Veli[1,2,3], Yi Luo[1,2,3], Mona Jarrahi[1,3], Aydogan Ozcan[1,2,3,4]†

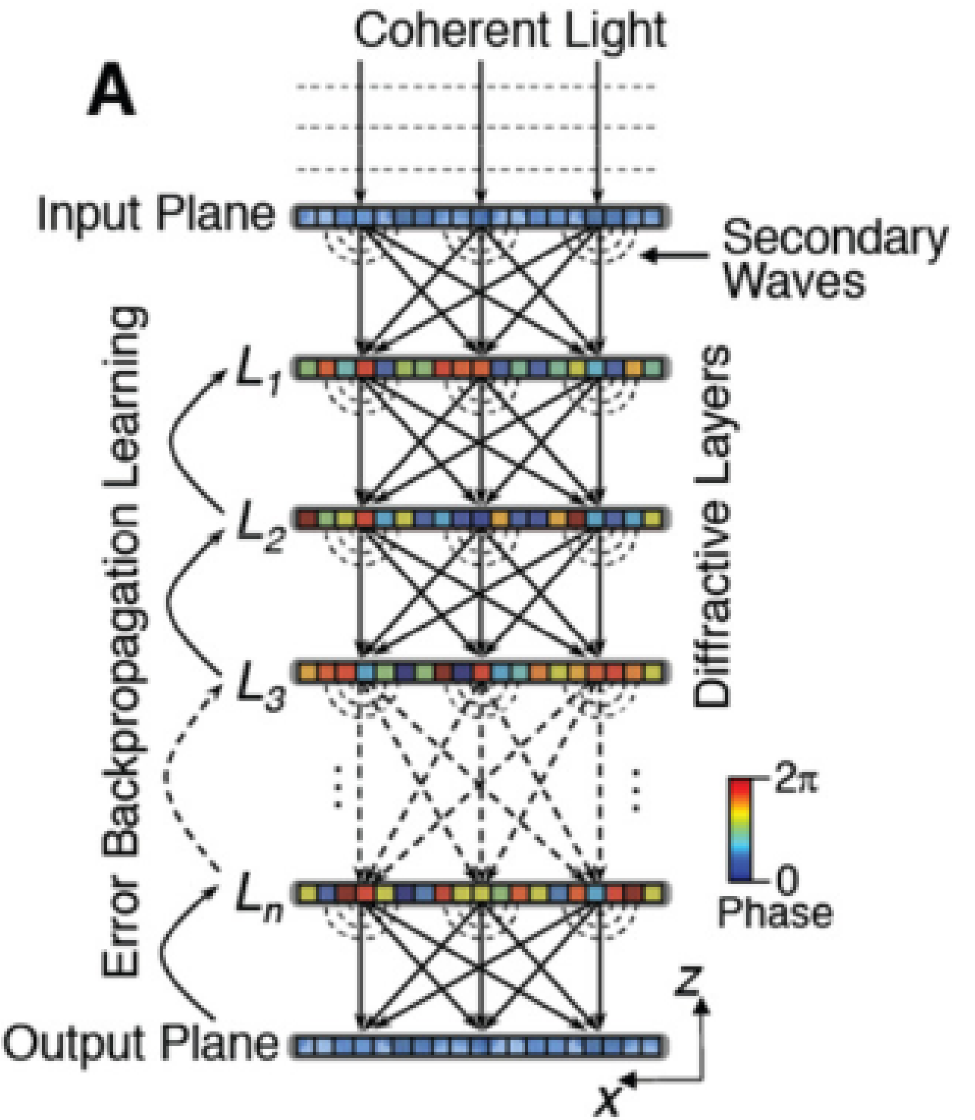
[1]Electrical and Computer Engineering Department, University of California, Los Angeles, CA, 90095, USA. [2]Bioengineering Department, University of California, Los Angeles, CA, 90095, USA. [3]California NanoSystems Institute (CNSI), University of California, Los Angeles, CA, 90095, USA. [4]Department of Surgery, David Geffen School of Medicine, University of California, Los Angeles, CA, 90095, USA.



Russell Pollari – September 10, 2018 - TDLS

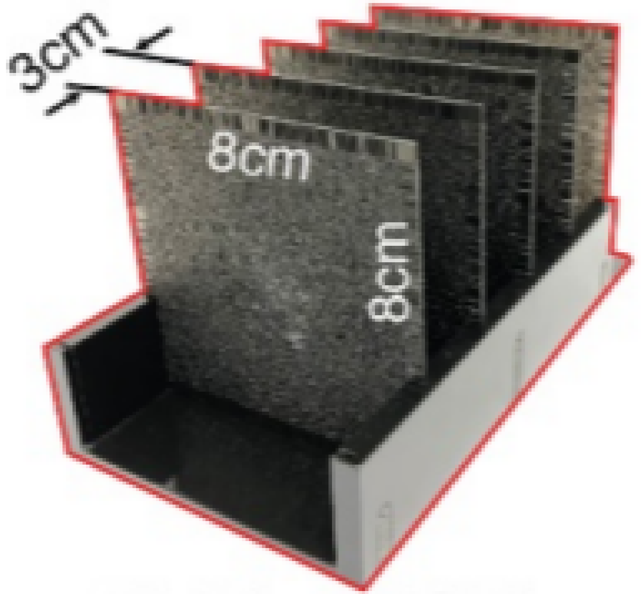
Diffractive Deep Nueral Network

- Diffractive Deep Neural Network (D²NN)
- **Input**: coherent light souce (Laser)
- **Layers**: transmissive, 3d printed filters
- **Output**: Intensity profile of filtered light

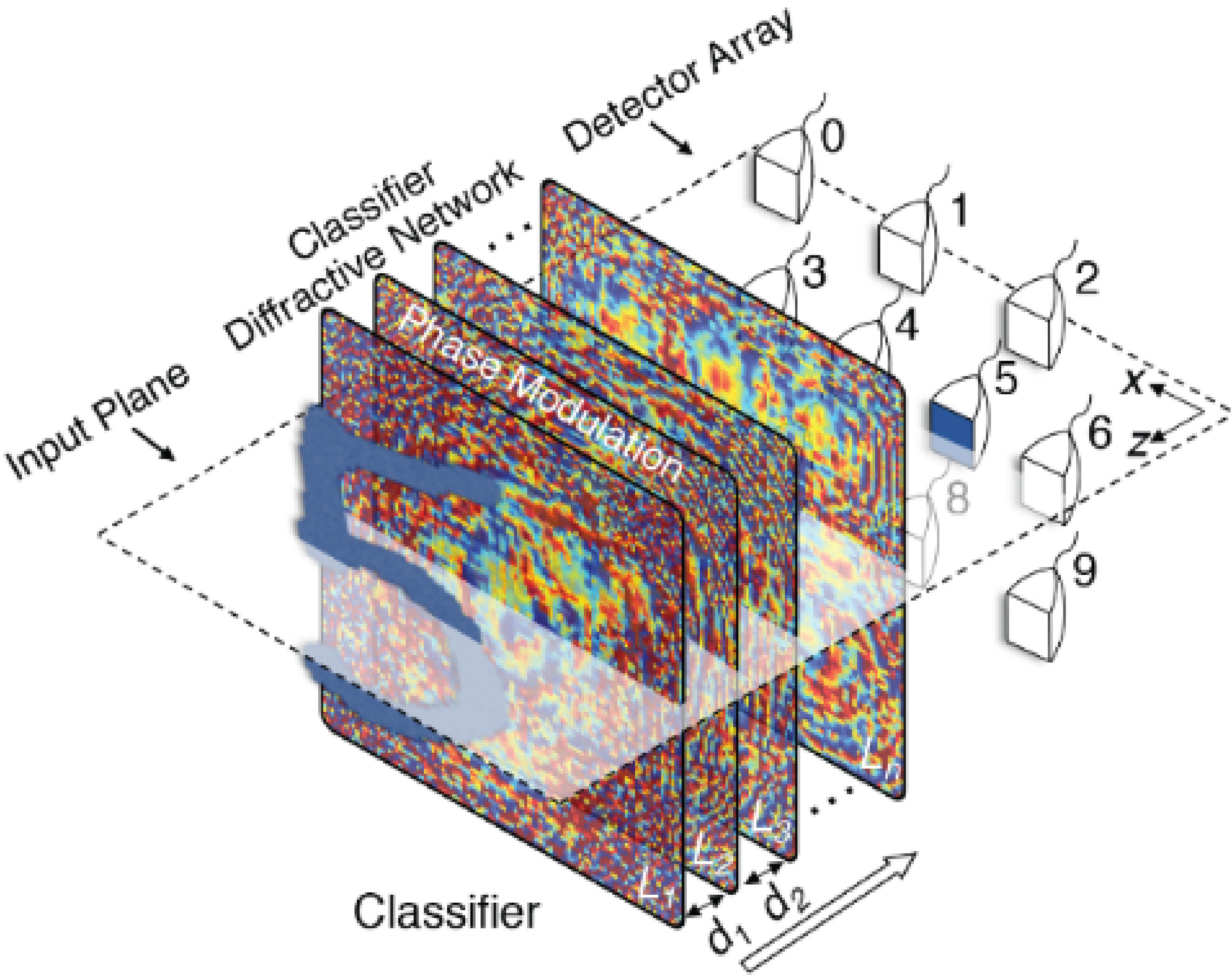


Setup

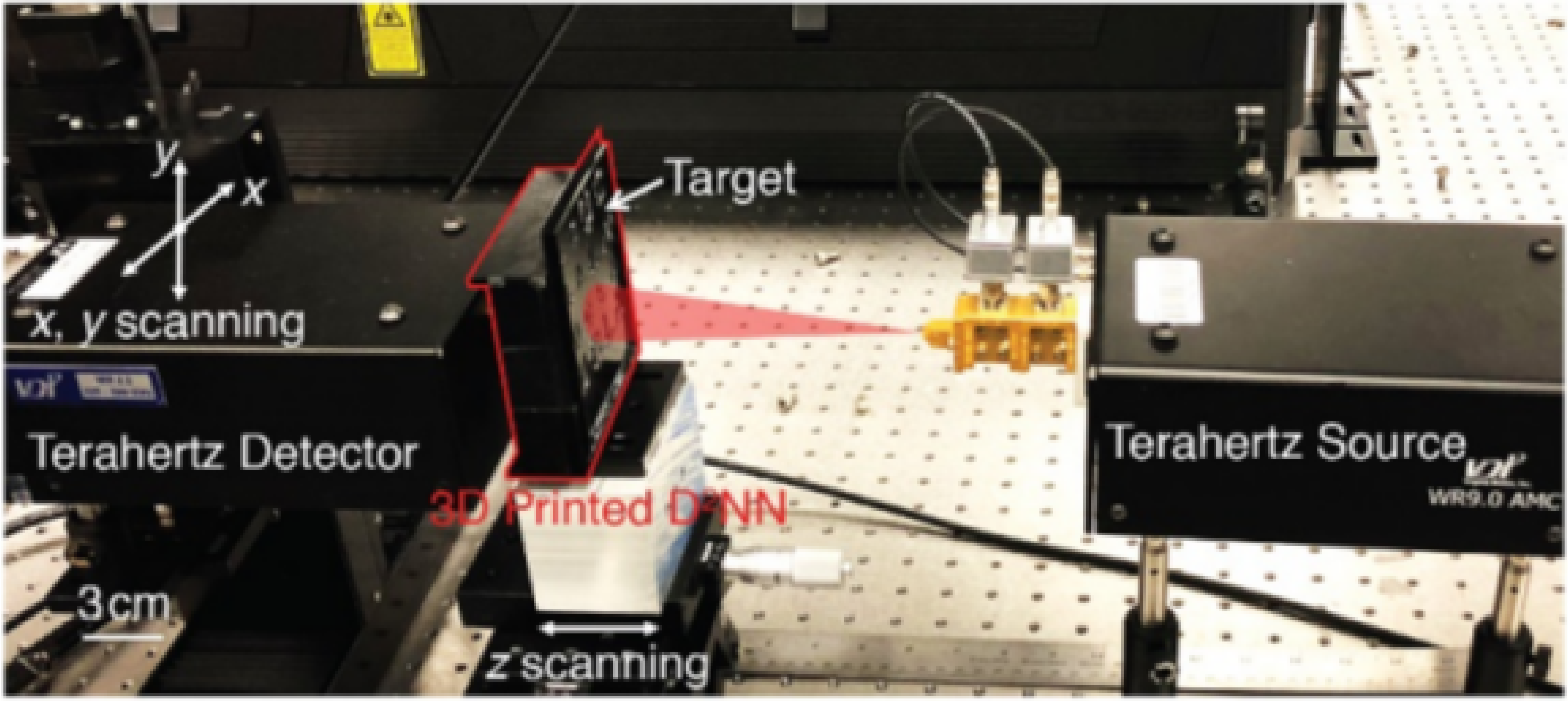
- Series of transmissive filters



3D Printed D^2NN
(Classifier)



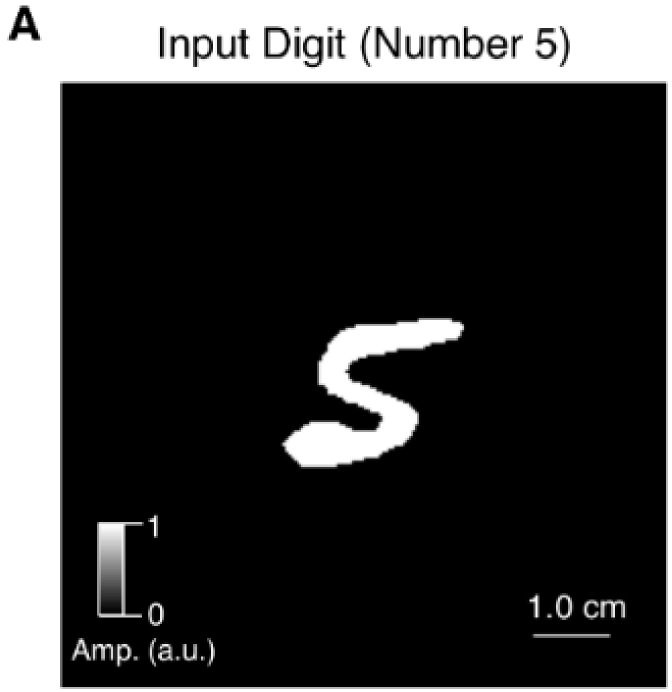
Setup

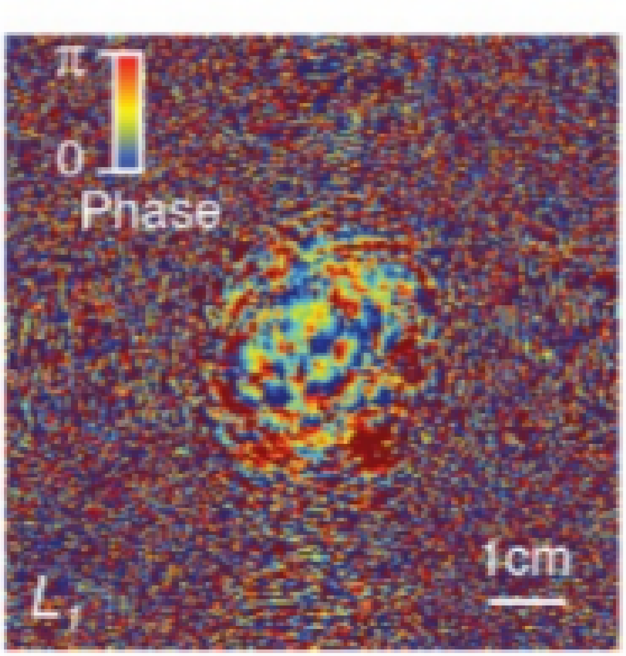

y
x
Target
x, y scanning
Terahertz Detector
3D Printed D²NN
3cm
z scanning
Terahertz Source
WR9.0 AMC

The physics

$$E(r) = A(r)e^{i\phi(r)}$$

$$T(r) = A(r)e^{i\phi(r)}$$

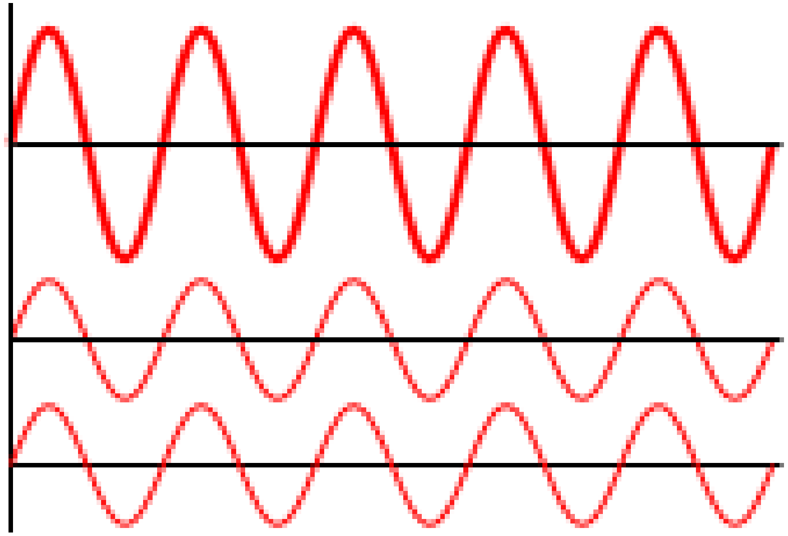


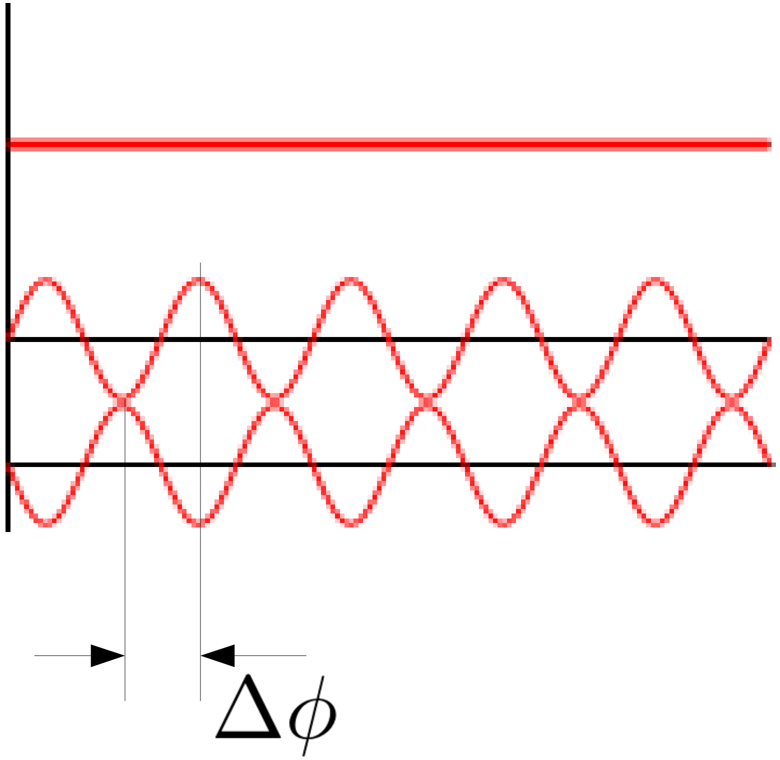


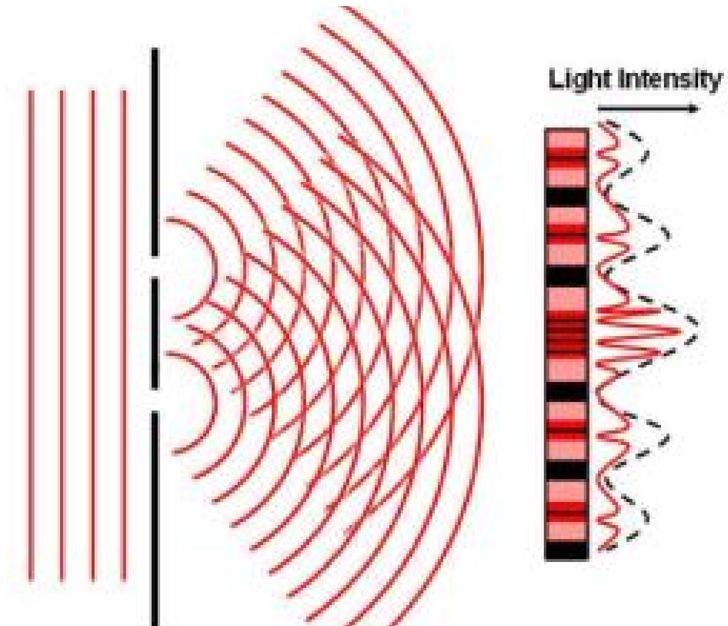
Free space
propagation

$$T(r)E(r) = A(r)A^l(r)e^{i(\phi(r)+\phi^l(r))}$$

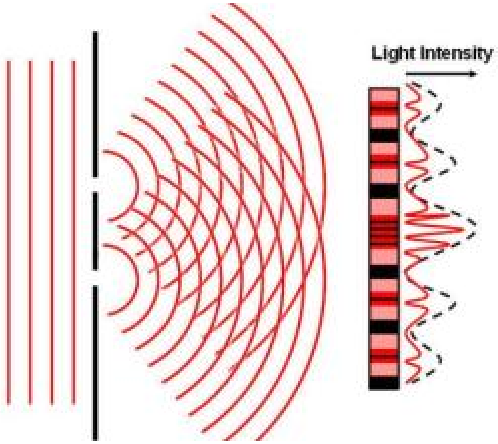
The physics (diffraction)

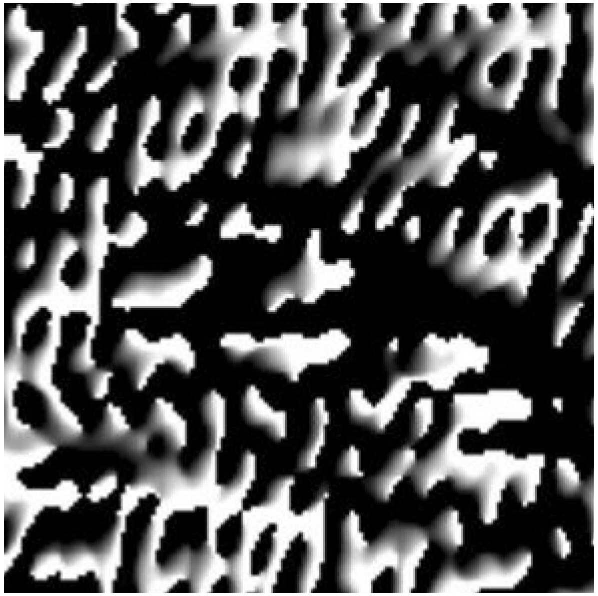






The physics (diffraction)





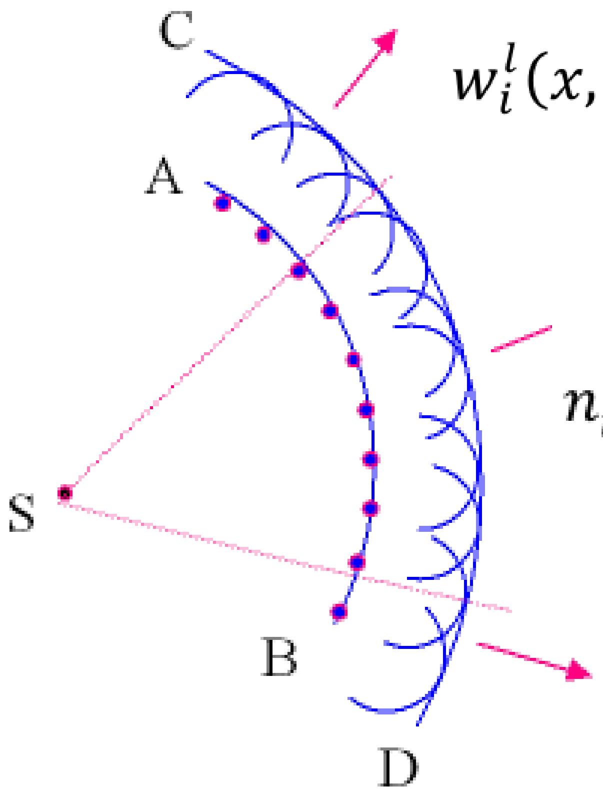
Propagation + diffraction

$$E(r) = A(r)e^{i\phi(r)}$$

$$I(r) = |E(r)|^2$$

The “neurons”

- **Huygen’s principle:** Each point on wave can be treated as secondary wave
- “neuron” is source of secondary wave



$$w_i^l(x,y,z) = \frac{z-z_i}{r^2}\left(\frac{1}{2\pi r}+\frac{1}{j\lambda}\right) exp\left(\frac{j2\pi r}{\lambda}\right)$$

(Free-space * transmission coef. of nueron * input wave)

$$n_i^l(x,y,z) = w_i^l(x,y,z)\cdot t_i^l(x_i,y_i,z_i)\cdot \sum_k n_k^{l-1}(x_i,y_i,z_i)$$

$$= w_i^l(x,y,z)\cdot |A| \cdot e^{j\Delta\theta}$$

$$t_i^l(x_i,y_i,z_i) = a_i^l(x_i,y_i,z_i) exp(j\phi_i^l(x_i,y_i,z_i))$$

Training

- "**phase-only**" diffraction - ignore optical losses at each layer

$$t_i^l(x_i, y_i, z_i) = a_i^l(x_i, y_i, z_i) exp(j\phi_i^l(x_i, y_i, z_i))$$

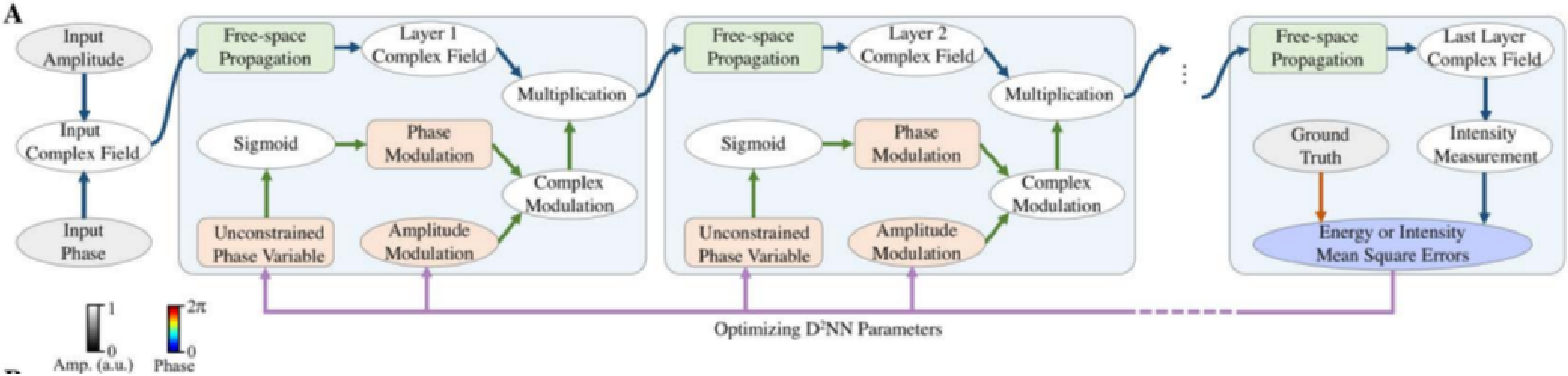
- Stochastic gradient decent (SGD)

$$E(\phi_i^l) = \frac{1}{K}\sum_k (s_k^{M+1} - g_k^{M+1})^2$$

(measured intensity – target intensity)

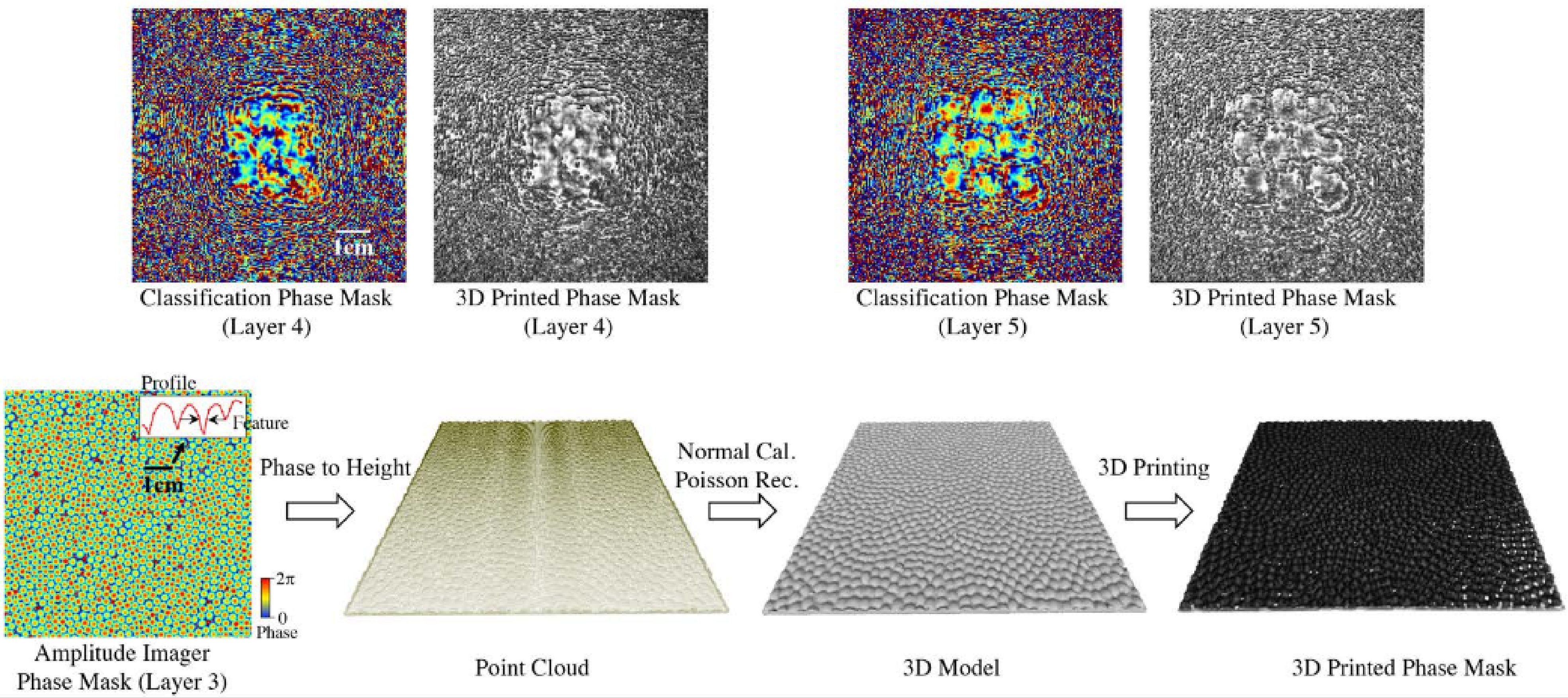
$$\min_{\phi_i^l} E\,(\phi_i^l),\ \ s.t. \qquad 0 \le \phi_i^l < 2\pi.$$

Training


A
Input Amplitude
Input Complex Field
Input Phase
Free-space Propagation
Layer 1 Complex Field
Multiplication
Sigmoid
Phase Modulation
Complex Modulation
Unconstrained Phase Variable
Amplitude Modulation
Free-space Propagation
Layer 2 Complex Field
Multiplication
Sigmoid
Phase Modulation
Complex Modulation
Unconstrained Phase Variable
Amplitude Modulation
Free-space Propagation
Last Layer Complex Field
Ground Truth
Intensity Measurement
Energy or Intensity Mean Square Errors
Optimizing D²NN Parameters
1
0
Amp. (a.u.)
2π
0
Phase

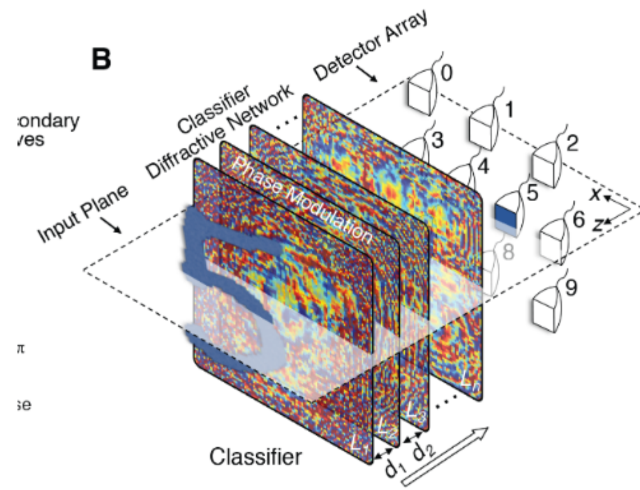
3D printing the layers

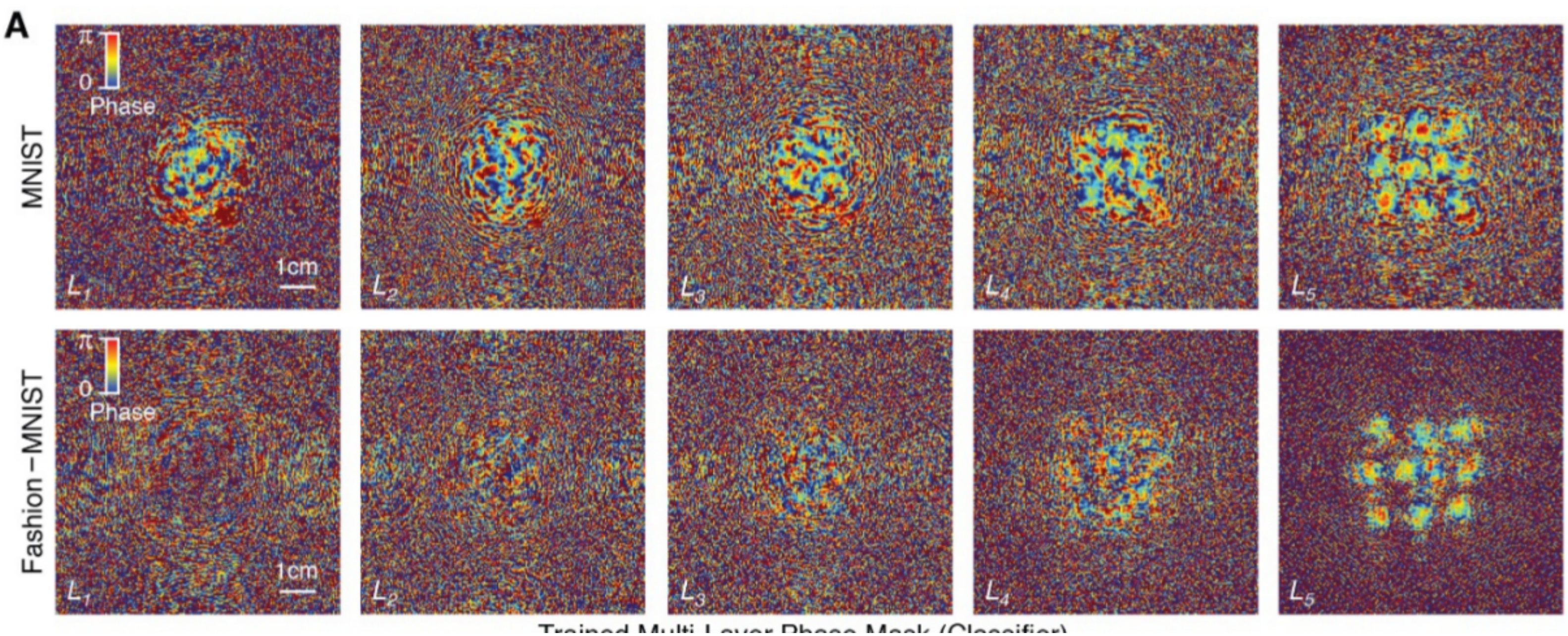
$$\Delta z = \frac{\lambda \phi}{2\pi \Delta n}$$

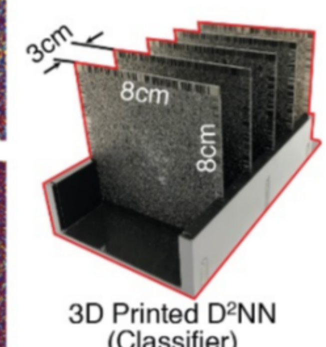


Experiments - MNIST

- Trained to map input digits to ten detector regions
- Digits encoded into amplitude of input field

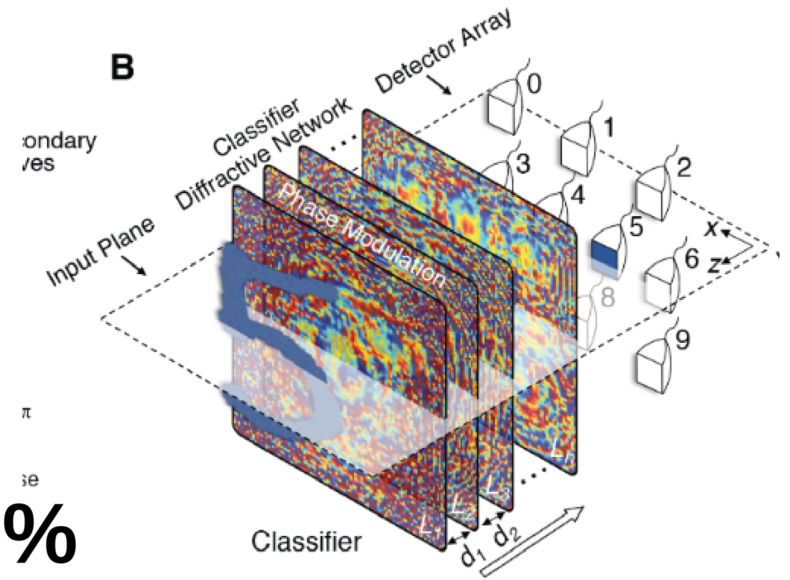






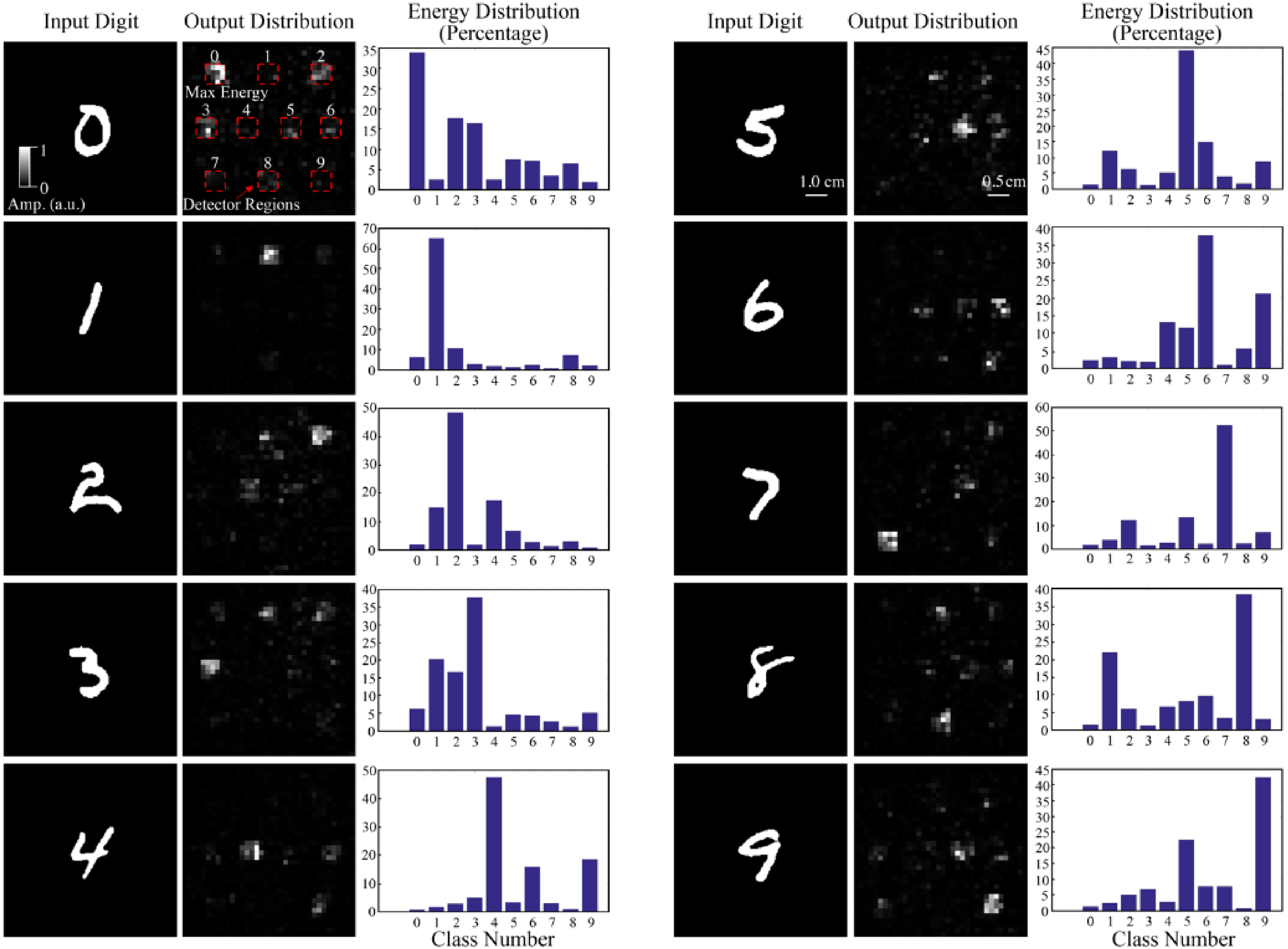
Experiments - MNIST

- 5 Layers: 8cm by 8cm
- Seperated by 3cm
- Neurons: 400um x 400um
- Numerical simulations: **91.75%**



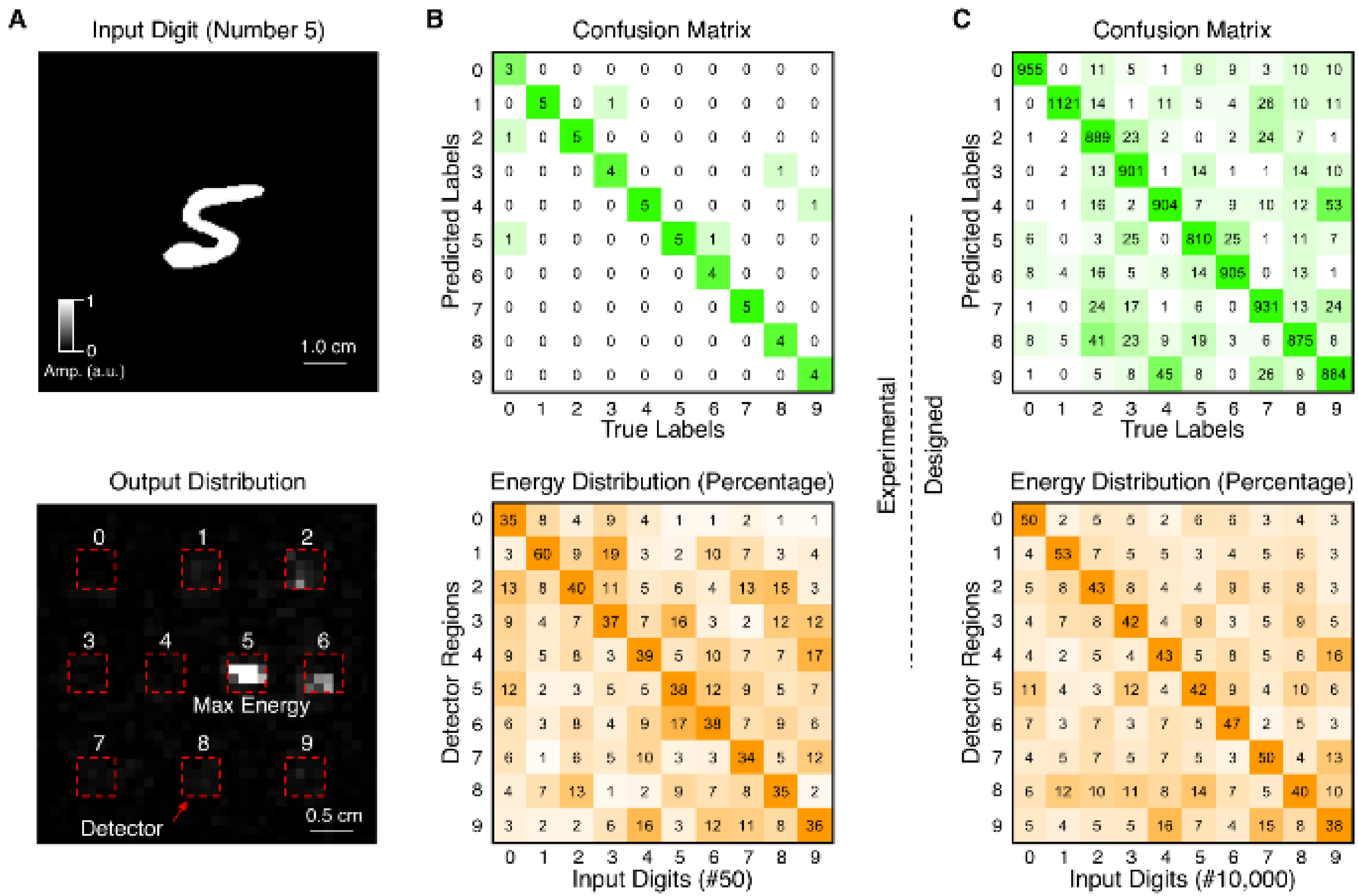
- Adding two more layers
  “transfer learning”: **93.39%**

Experiments - MNIST



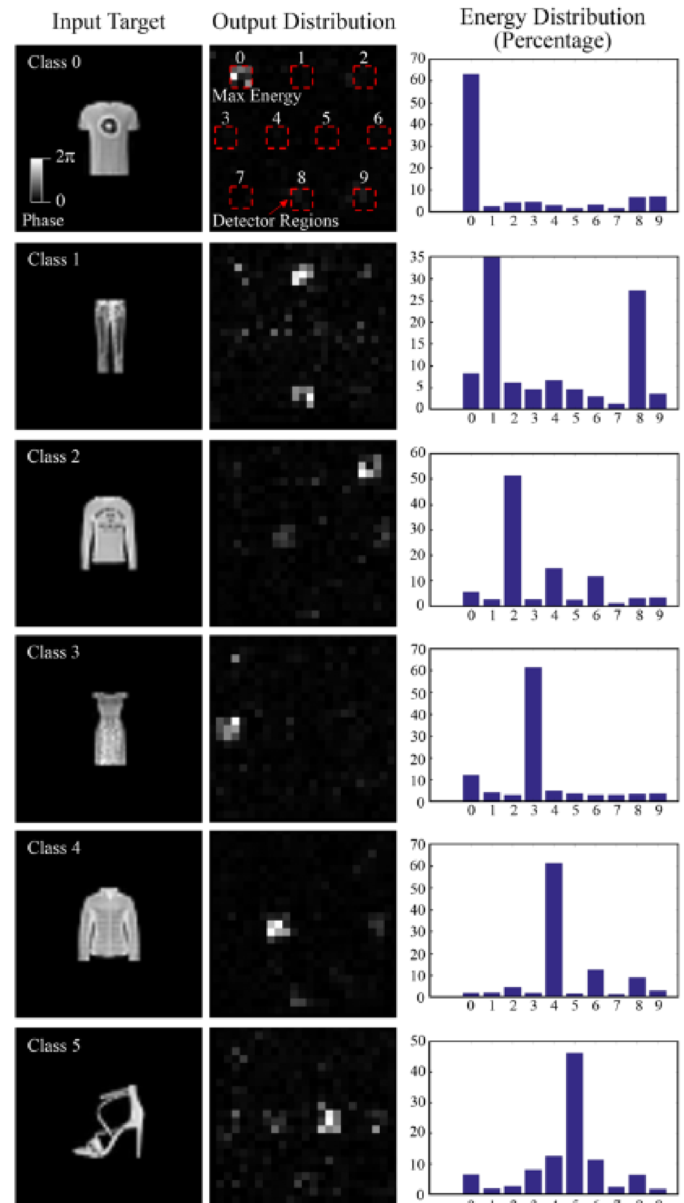
Experiments - MNIST

- Experimentally tested with 50 images that were classified correctly in simulations
- **88%** agreement with simulations



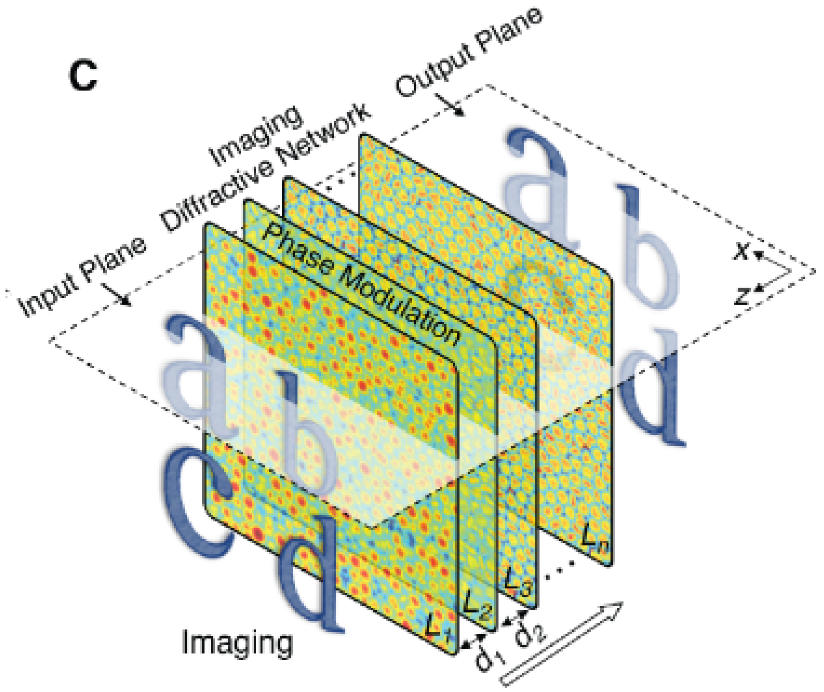
Experments – Fasion MNIST

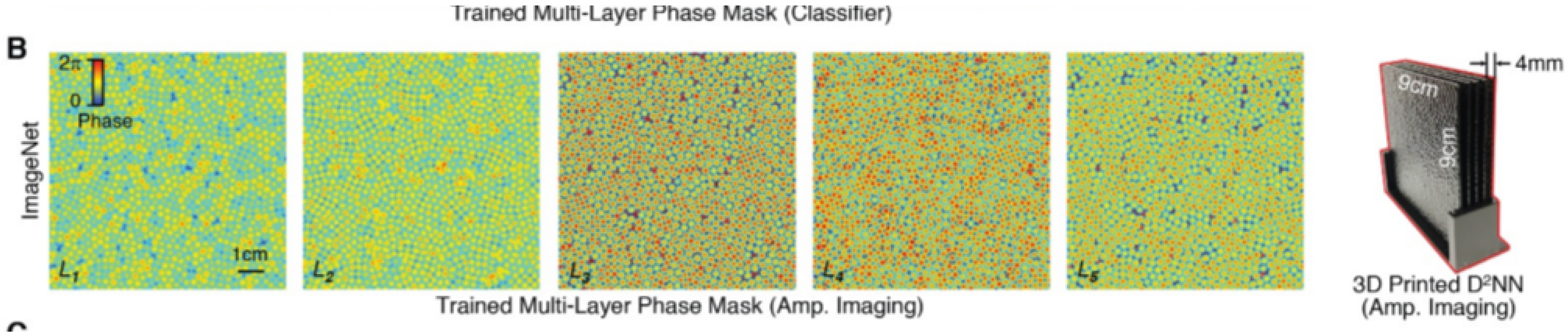
- Ten clases (t-shirt, shirts, coats) etc.
- Input encoded into phase of input
- Simulation:
    - 5 layers: **81.13%**
    - 10 layers: **86.60%**
- Experient:
    - 5 layers
    - 90% match with simulation



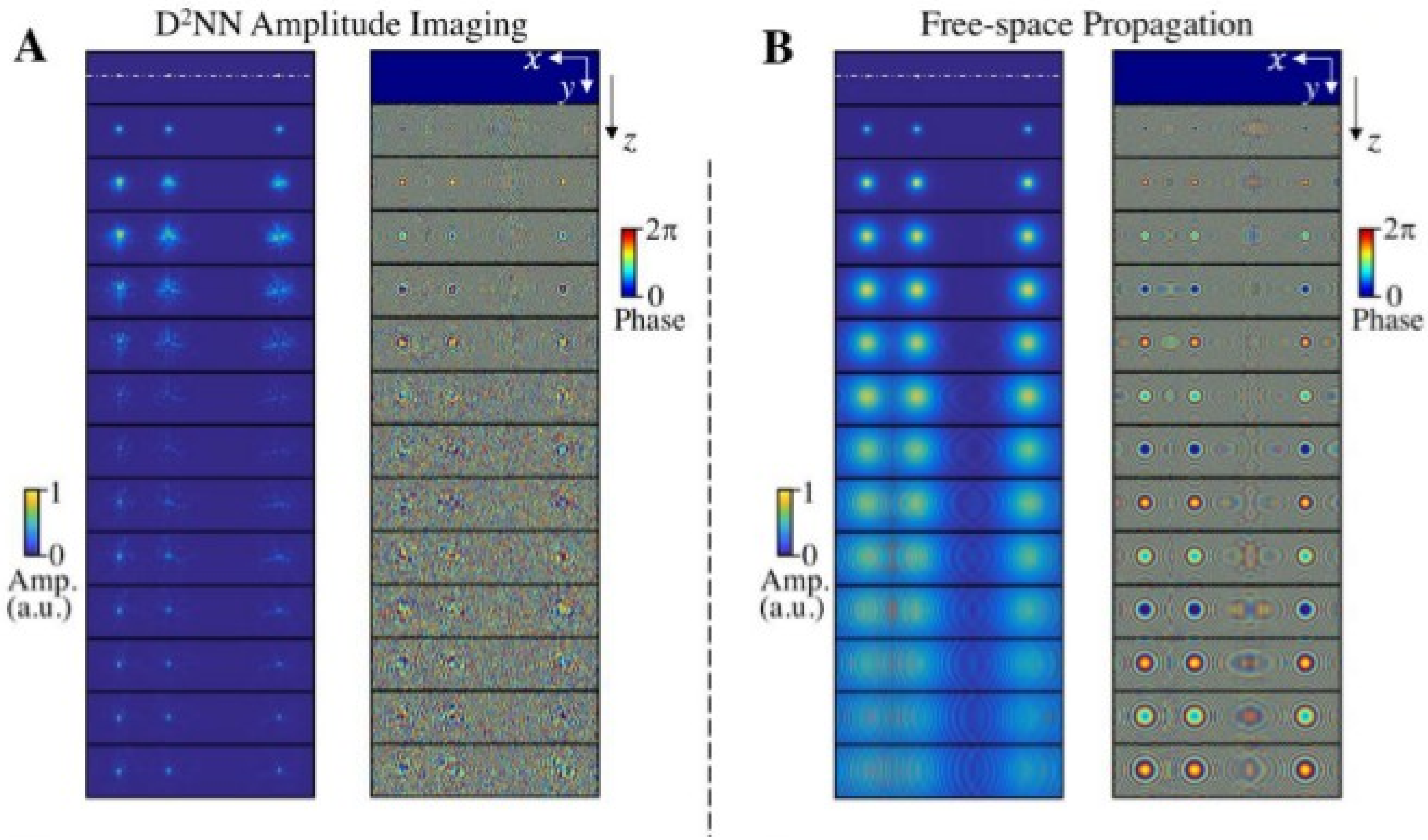
Experiments - Imaging

- Unit-magnification image
- ImageNet database

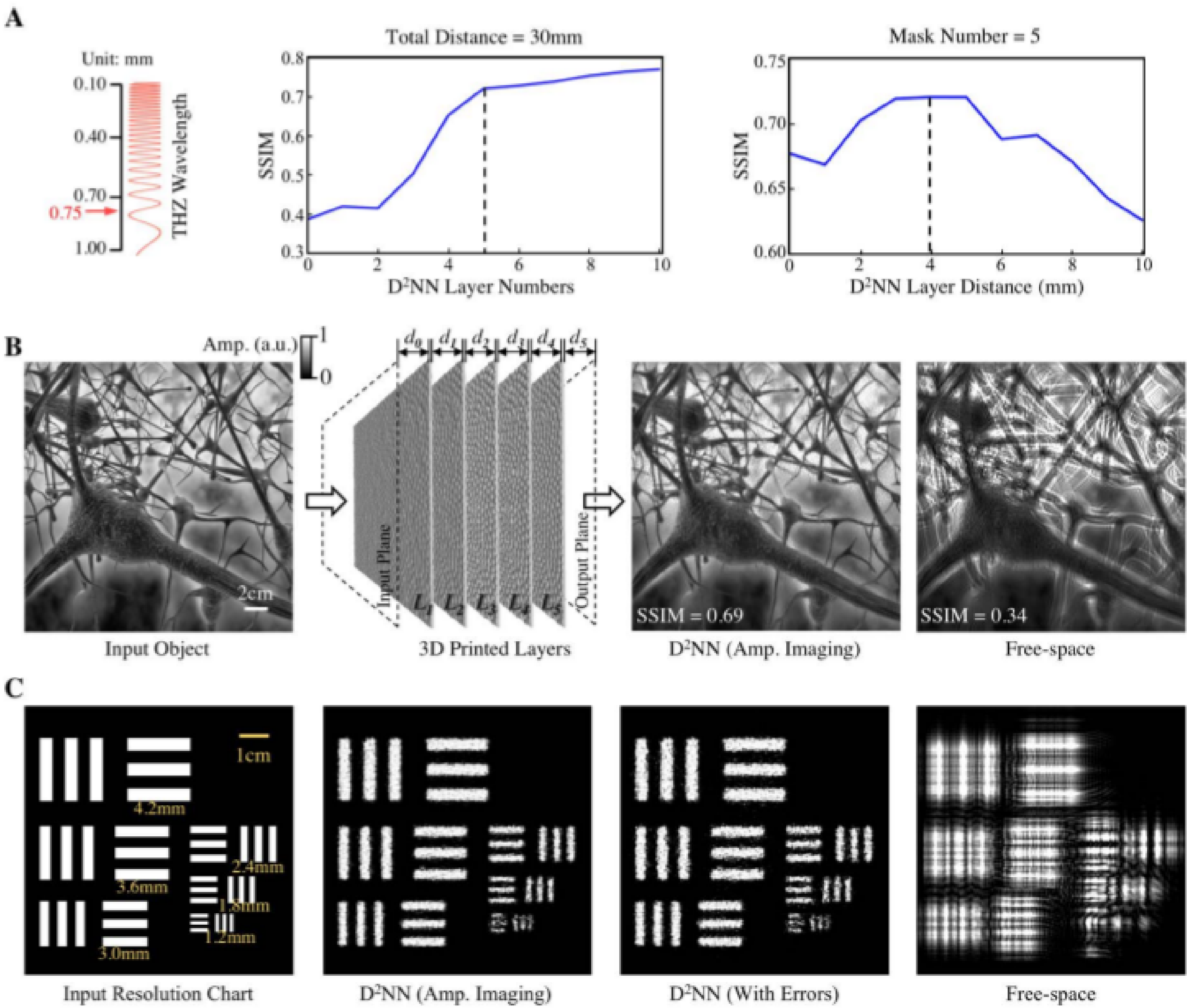




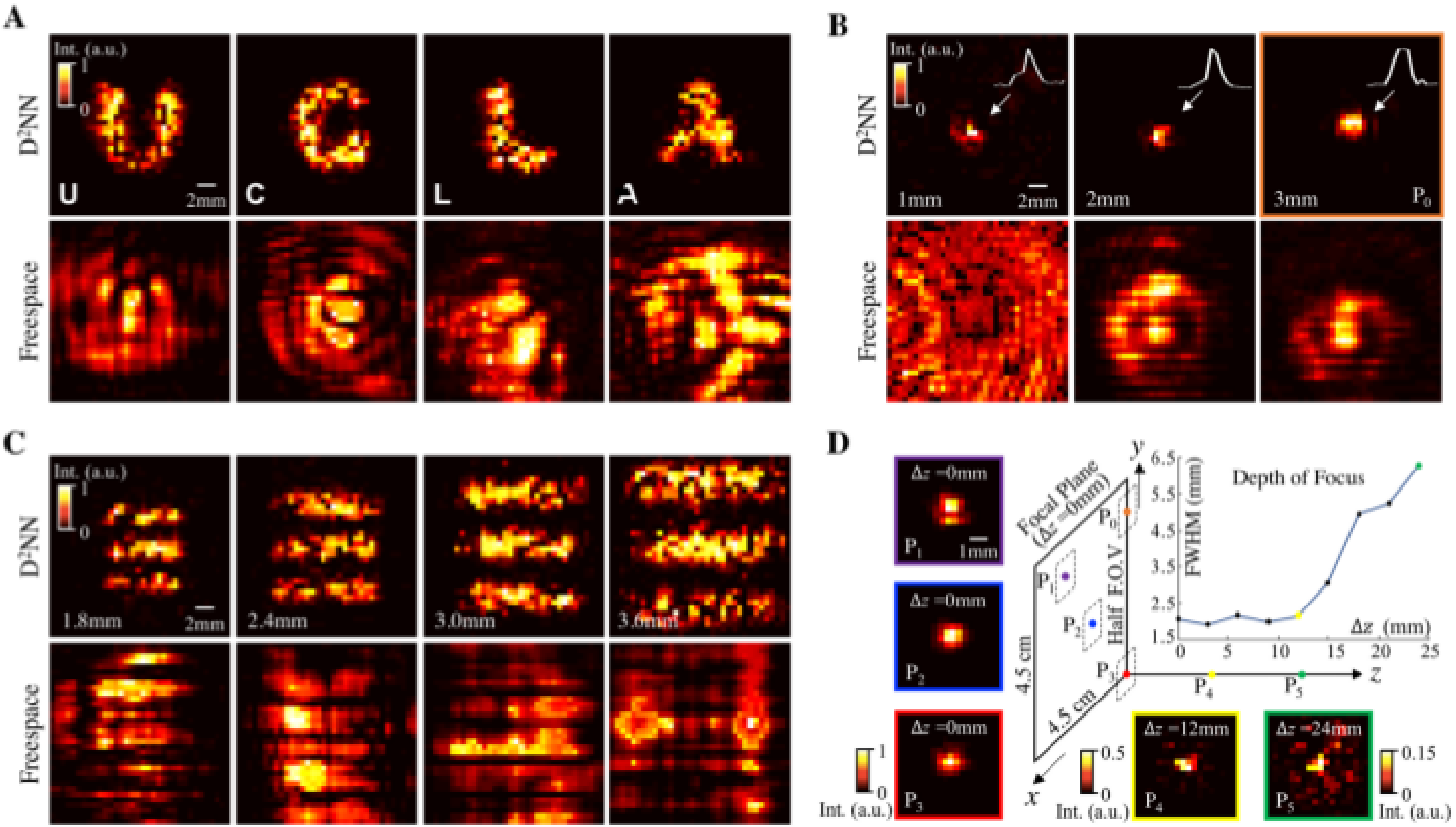
Experiments - Imaging



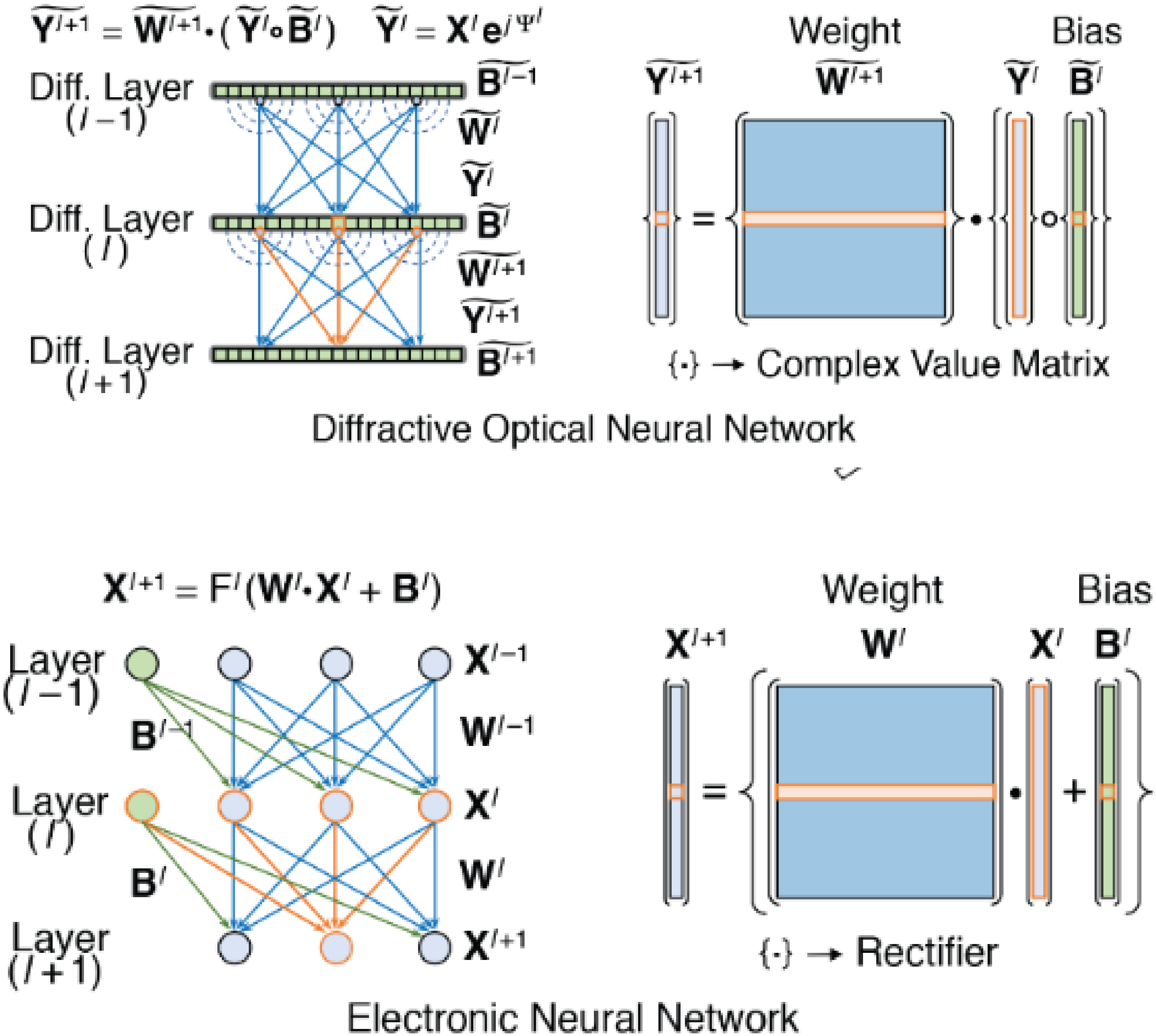
Experiments - Imaging



Experiments - Imaging



Comparison to neural nets



Comparison to neural nets

- Inputs are complex-valued, determined by wave-interference
- Neuron = pixel which modies phase and amplitude
- No non-linearity?
  - Interference is linear..
  - Could use non-linear optics, but requires much higher intensities

Final thoughts

Pretty cool, but should this be labelled a neural net?