Image classification using collective modes of a two-dimensional array of photonic-crystal nanolasers

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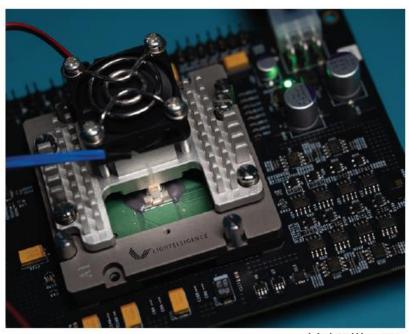




Motivation

- High performance computing systems and artificial intelligence systems consume huge amounts of energy.
- Big concern in the context of climate change.
- Photonic systems can be
 - much faster,
 - consume much less energy.

Photonic integrated circuits are commercially available



Lightelligence

INDUSTRY

Lightelligence Unveils New Chip

Optics and Photonics News 2022

PACE (Photonic Arithmetic Computing Engine) processes intensive matrix multiplications (a bottleneck in many "hard" computing problems) at much faster speeds than an electronic processor.

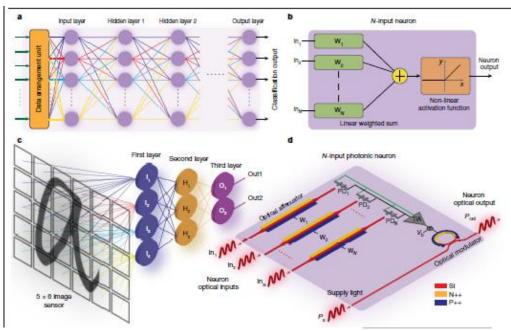
PIC is packaged with an electronic integrated circuit to handle other tasks.

Article

An on-chip photonic deep neural network

for image classification

Nature | Vol 606 | 16 June 2022 | **501**



NATURE COMMUNICATIONS | (2022)13:123

https://doi.org/10.1038/s41467-021-27774-8

OPEN

An optical neural network using less than 1 photon per multiplication

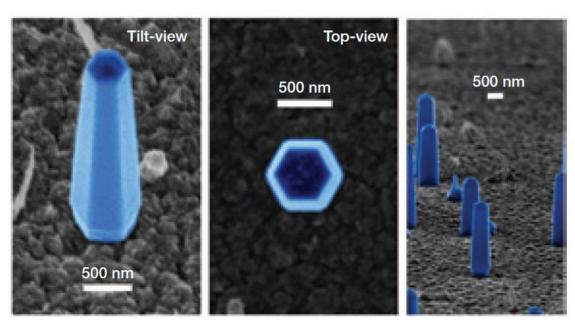
Tianyu Wang ^{1⊠}, Shi-Yuan Ma ¹, Logan G. Wright ^{1,2}, Tatsuhiro Onodera ^{1,2}, Brian C. Richard &

Photonic computing systems need the development of tiny laser light sources that can be integrated on chips

Semiconductor nanolasers have three key advantages:

- Very small
 - Very low threshold
 - Room Temp. operation

Subwavelength lasing: transverse size $< \lambda$



R. Chen et al, Nat. Photonics 2010

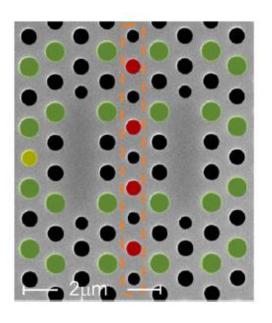
Nanolaser array

2x2 Photonic crystal cavities in an Indium Phosphide (InP) membrane, with embedded InGaAsP quantum wells

The coupling strengths can be tuned by changing the parameters of the structure

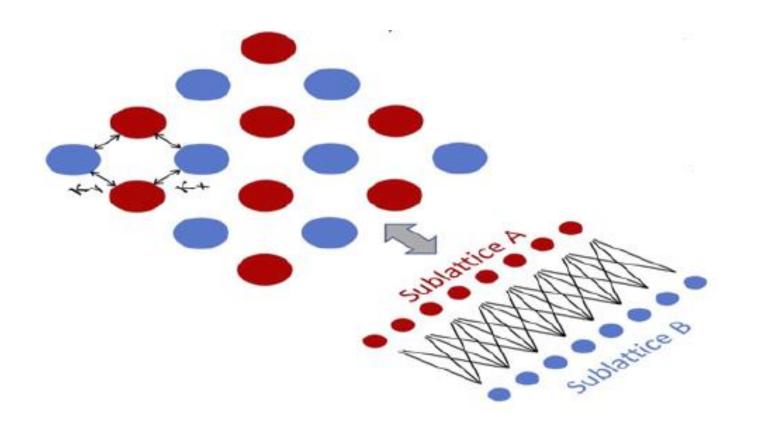
Dielectric material with periodic structures (holes)

Optical cavities coupled by proximity



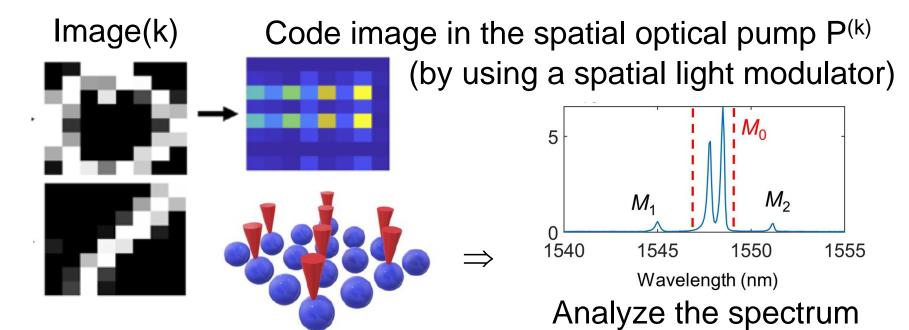
Scanning electron microscope (SEM) image of 2 nanocavities (K. Ji et al, Nat. Comm. 2023)

Schematic representation of a 4 x 4 array



⇒Two layer photonic ANN

Nanolaser array for binary classification of low-resolution images



If a "selected-mode" lases: image is classified as 0, else 1

Key issue: good "spectral gap".

Machine learning parameter optimization.

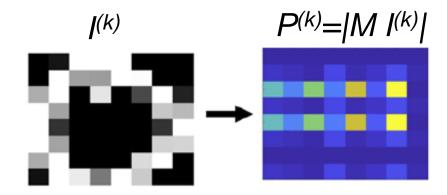


Model

$$i\frac{da_{m,n}}{dt} = \kappa_x(a_{m-1,n} + a_{m+1,n}) + \kappa_y(a_{m,n-1} + a_{m,n+1}) + i(g_{m,n} - \gamma)a_{m,n}$$

Spatial pump pattern: $P = \{g_{m,n}\}$

Transformation matrix *M*: P = |M|; *I* it the matrix of pixel values.



$$\boldsymbol{H} = \sum_{m,n} K_1 |a_{mn}\rangle\langle a_{m+1,n}| + K_2 |a_{mn}\rangle\langle a_{m+1,n}| + h.c. + i(g_{mn} - \gamma)|a_{mn}\rangle\langle a_{m,n}|$$

- All the eigenvalues with $\Im[\lambda_i] < 0$
- At least one eigenvalue with $\Im[\lambda_i] > 0$

- → STABILITY (OFF STATE)
- → INSTABILITY (ON STATE)



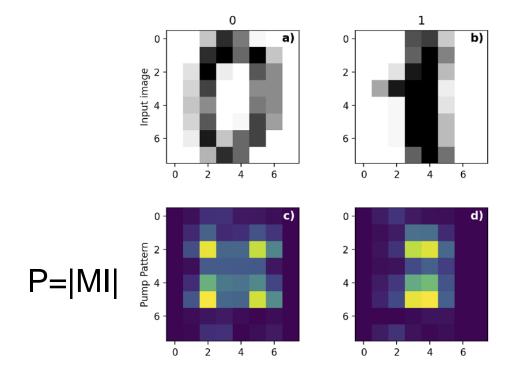
Implementation

- We simulate **8x8** identically diffusively coupled nanocavities.
- 64 rate equations for the complex amplitudes a_{mn} .
- Images to be classified need to be re-sized to 8x8.
- A more realistic model (including detunings) is needed to obtain experimentally good classification.
- Goal: find the 64 elements of matrix M (optical pump) $P^{(k)}=|MI^{(k)}|$, where $I^{(k)}$ is the pixel matrix of the kth image) that optimize the classification performance.



Data

- Hand-written digit dataset freely available at University of California-Irvine (UCI) ML repository.
- 360 images.
- 75% (270 images) for training, 25% (90 images) for testing.
- 8x8 image resolution.



Machine learning optimization

Minimization of the cost function using images of training set.

$$C = -\sum_{k \in \{+\}} \tanh \left(\eta \Delta \varepsilon^{(k)} \right) + \sum_{k \in \{-\}} \tanh \left(\eta \Delta \varepsilon^{(k)} \right)$$

{+} and {-} denote the two sets of images for which the "spectral gap" of kth image $\Delta \varepsilon^{(k)}$ is expected to be + or -.

$$\Delta \epsilon^{(k)} = \max_{i: \left| \Re\left[\epsilon_i^{(k)}\right] \right| \le \delta} \Im\left[\epsilon_i^{(k)}\right] - \max_{i: \left| \Re\left[\epsilon_i^{(k)}\right] \right| > \delta} \Im\left[\epsilon_i^{(k)}\right]$$

- $\varepsilon_i^{(k)}$ eigenvalues of Hamiltonian generated by image k.
- Selected modes have null or small real part.
- δ represents the spectral resolution of the detection system.

Results

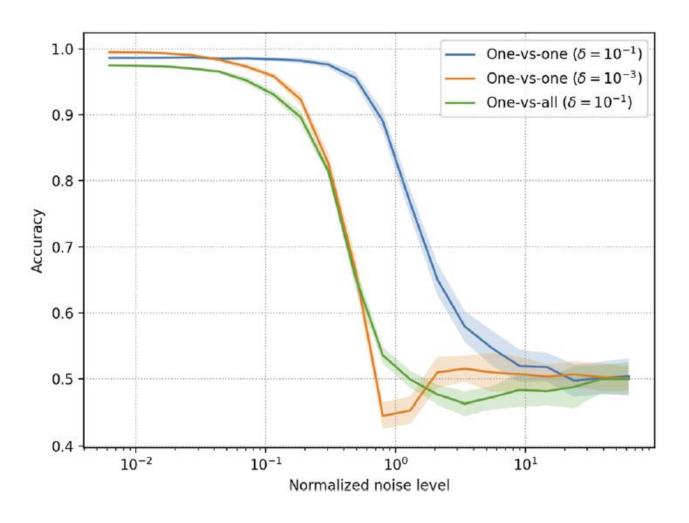
- Once the cost function was minimized using the images of the training set (about 24 hs on a 40 core cluster), M was used to classify the images of the training and testing sets.
- Tasks: distinguish 0s and 1s (one-vs-one classifier) and distinguish 0s and any other digit (one-vs-all classifier).

			One-v	rs-one	One-vs-all
	Resolution	δ	10^{-3}	10^{-1}	10 ⁻¹
(TP+TN)/total	Accuracy (%)	Train Test	100 98.9	98.9 97.8	97.8 96.7
TP/predicted yes	Precision (%)	Train Test	100 100	100 100	97.7 97.9
TP/actual yes (fraction of 0s correctly identified)	Recall (%)	Train Test	100 98	97.6 96.1	97.7 95.8

G. Tirabassi et al, APL Photonics 2022



Role of noise in the input image

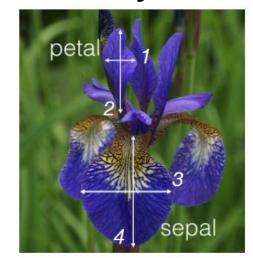


G. Tirabassi et al, APL Photonics 2022

To perform experiments with a 2x2 nanolaser array

Iris dataset: 4 features

150 measurements







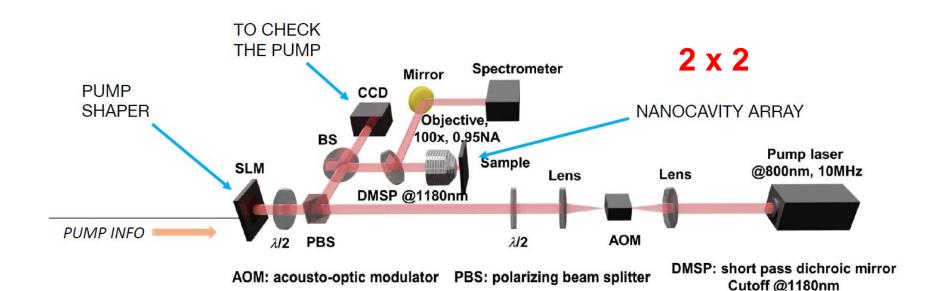


Iris Versicolor

Iris Setosa

Iris Virginica

Experiments



Experimental results are comparable with (and sometimes even better than) the simulation.

Kaiwen Ji, Giulio Tirabassi et al (in preparation)



Conclusions

- We have shown numerically that a nanolaser array can be used to implement in hardware a photonic artificial neural network able to classify *low-dimensional* data.
- Performance close to the state of the art (a perceptron or a random forest can achieve nearly 100% accuracy).



Thank you for your attention!









