Machine learning for design optimizations and prediction of optical chip performance

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Enablence Technologies Inc.

Photonics West

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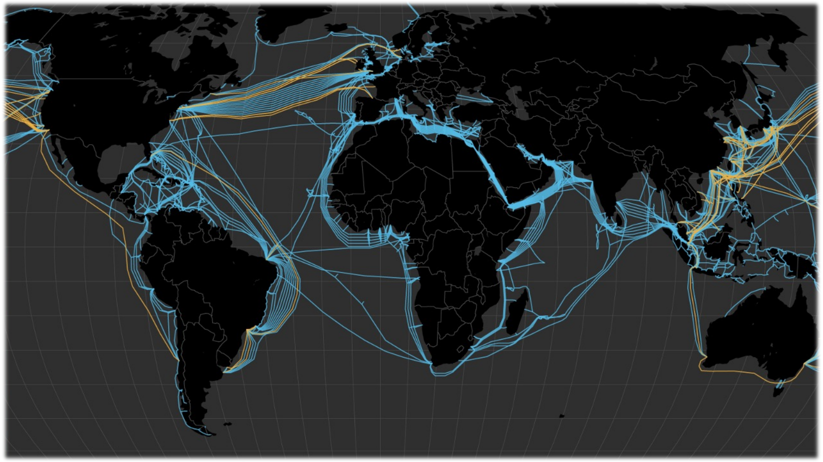
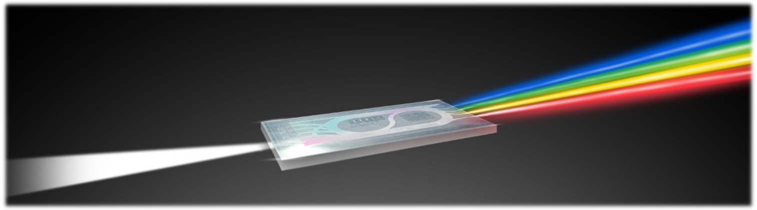
Introduction

Optical communication

- The deployment of wide-scale optical communication systems led to a phenomenal growth in information exchange.
- High-capacity optical fibers, combined with the use of integrated optical devices to control light, allow for optical networks with advanced routing and multiplexing capabilities.





Introduction

Artificial intelligence and machine learning

- Artificial intelligence (AI) and machine learning (ML) emerged as a powerful new approach for solving previously intractable problems.

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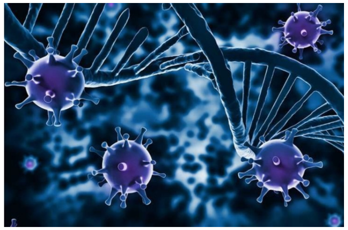

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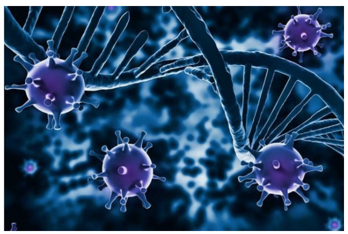

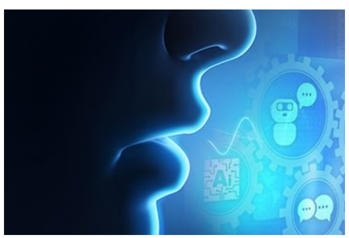

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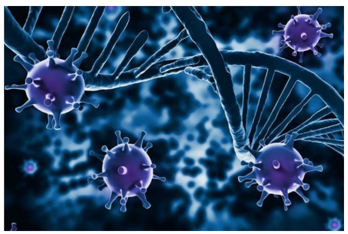

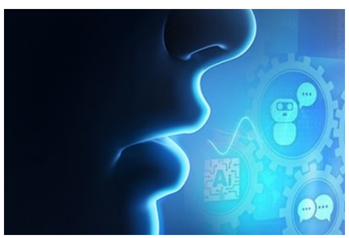

ML is able to capture essential features from vast amounts of high-dimensional data

Introduction

AI/ML in photonics

- The photonics industry has began adopting AI and ML techniques to further both research and deployment of optical technologies.

Introduction
AI/ML in photonics

Enablence

- The photonics industry has began adopting AI and ML techniques to further both research and deployment of optical technologies.
- Advances have been made in:
  - Deep learning for inverse design

nature photonics

Review Article | Published: 26 October 2018

Inverse design in nanophotonics

Sean Molesky, Zin Lin, Alexander Y. Piggott, Weiliang Jin, Jelena Vucković & Alejandro W. Rodriguez

Introduction
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nature photonics

Research Article Vol. 4, No. 11 / November 2017 / *Optica* 1437

optica

Deep learning microscopy

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Introduction

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  - Deep learning microscopy
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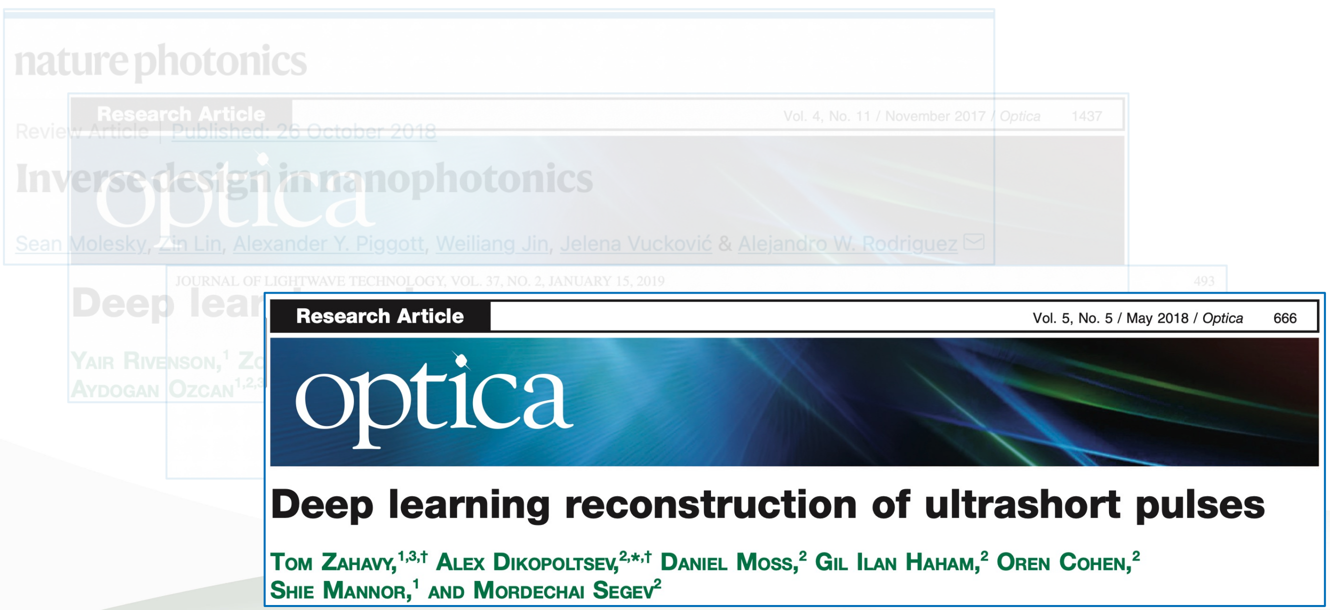
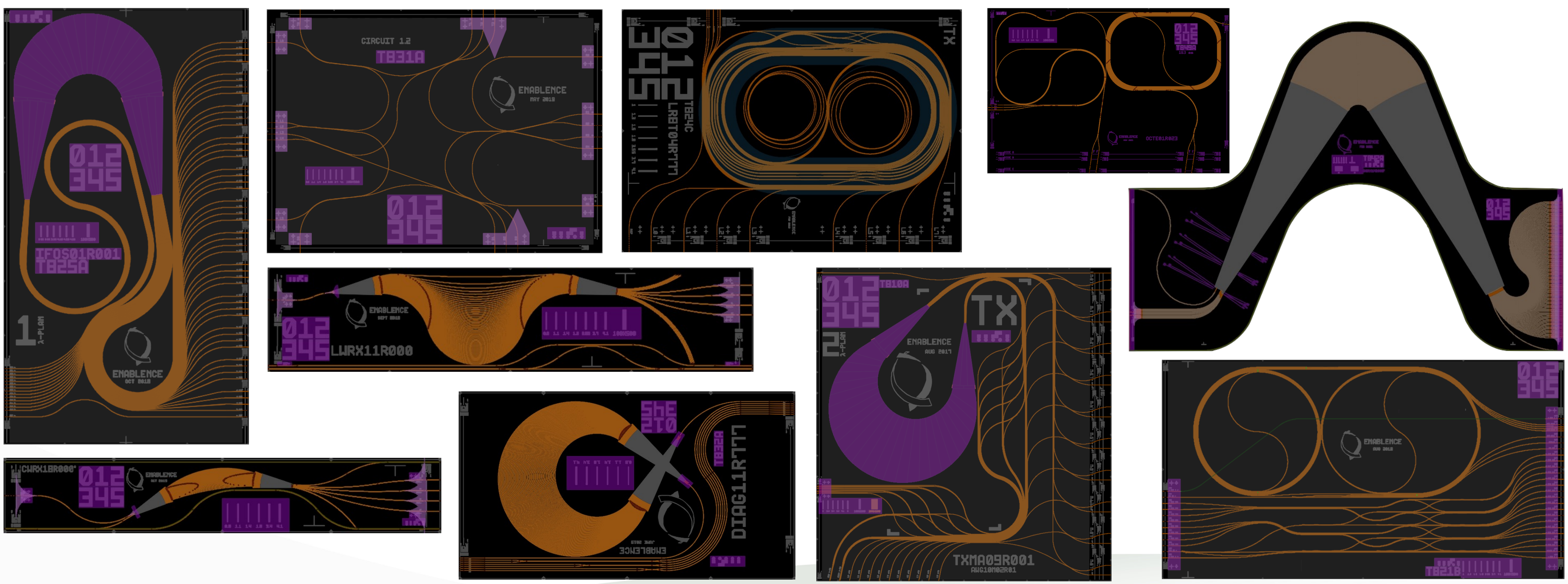
  - Deep learning microscopy
  - Machine learning in optical communication and networking
  - Deep learning in ultrafast optics



Introduction

Photonic integrated circuits

- Photonic integrated circuits have grown into a powerful and versatile platform that is able to meet the challenging demands of today's high-speed communication and advanced vision systems.
- Photonic circuits possess high optical performance and are well suited for both monolithic and hybrid integration.



Introduction

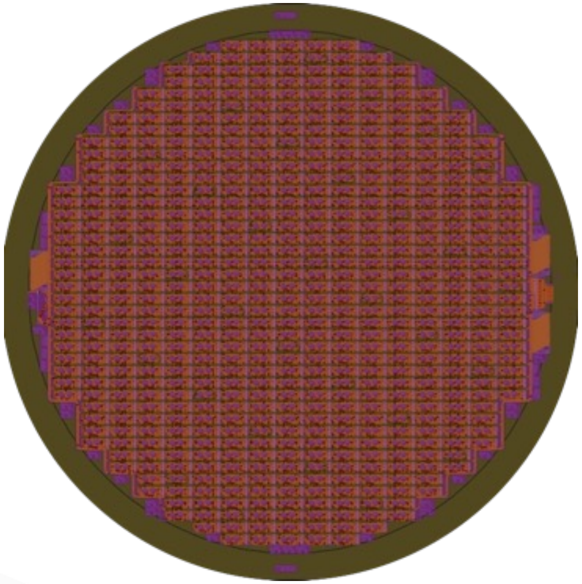
Volume production of photonic circuits

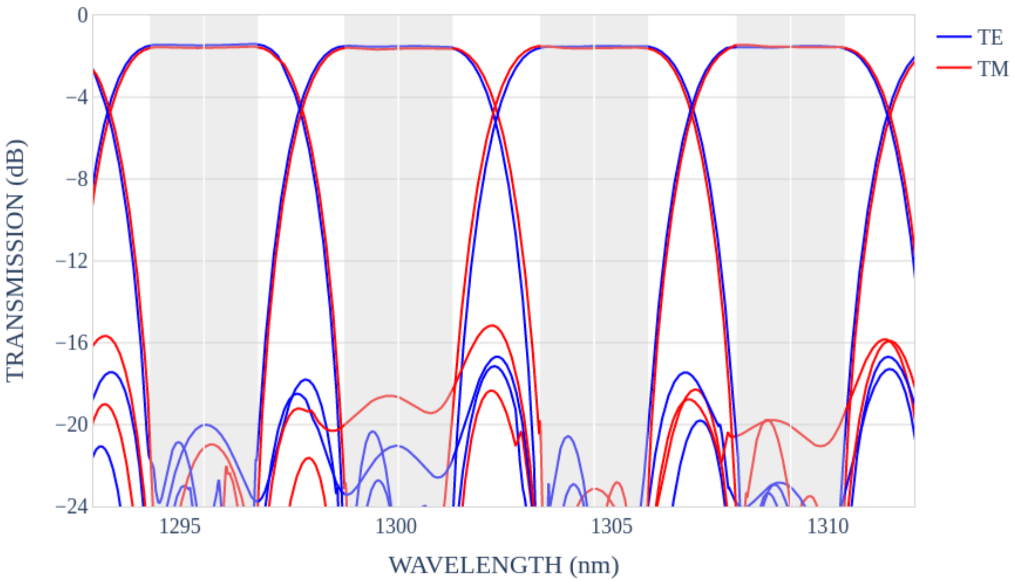
- The key to accelerated adoption of photonics is achieving reproducible performance – a significant challenge in the photonics industry.
- Traditionally, the problem of performance inhomogeneity stemming from process variations has been handled by relying on 100% optical testing of devices.
- Today, we:
  - Present how the use of AI/ML has revolutionized the field of photonic integrated circuit design and manufacturing.
  - Describe our use of deep learning to optimize the multi-dimensional design parameter space for hundreds of optical chips on a production mask.
  - Discuss our approach of using ML to predict the performance of optical devices by wafer probing.
  - Show how the use of AI/ML allows us to achieve an unprecedented control over our fabrication process, and thus consistently high performance of optical chips at high production volumes.

Design optimizations

Volume production of photonic circuits

- Photonic integrated circuits have been widely used to realize high-performance wavelength division multiplexing (WDM) devices for datacom and telecom applications.
- A typical production wafer contains hundreds of optical devices:

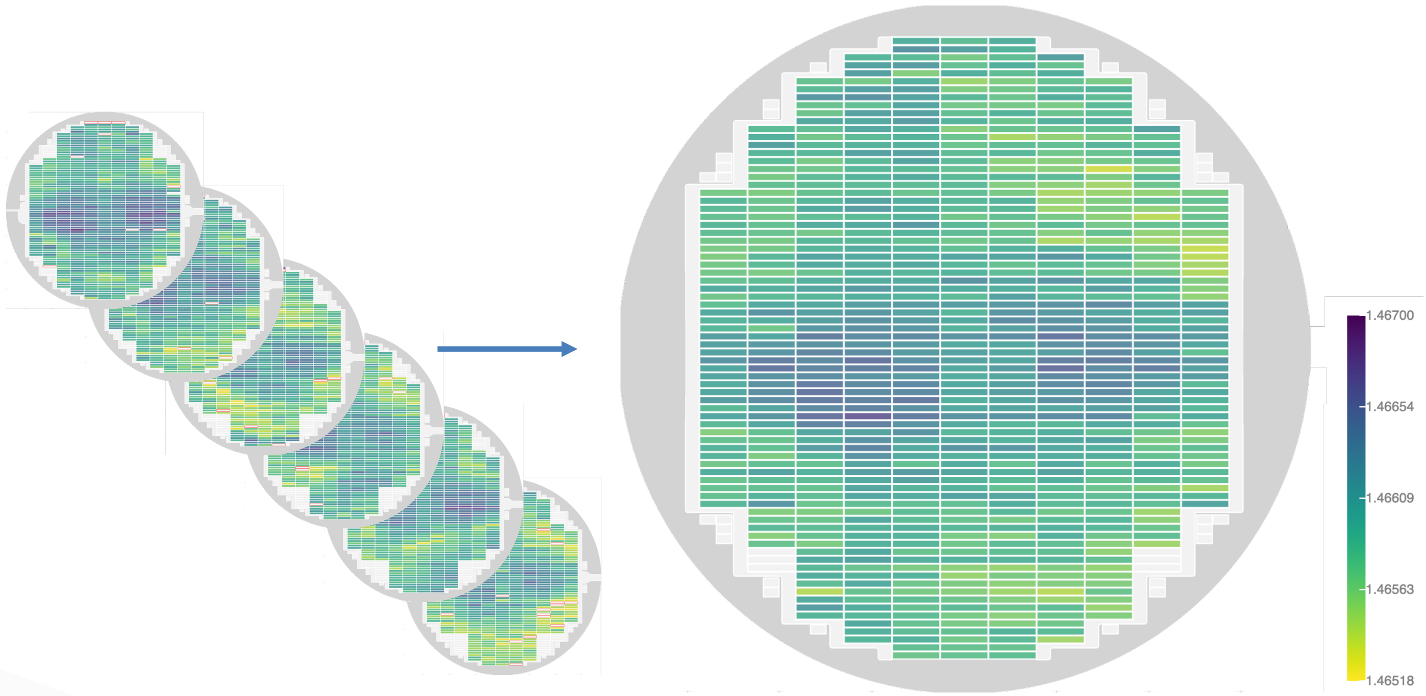




Design optimizations

The challenge of process uniformity

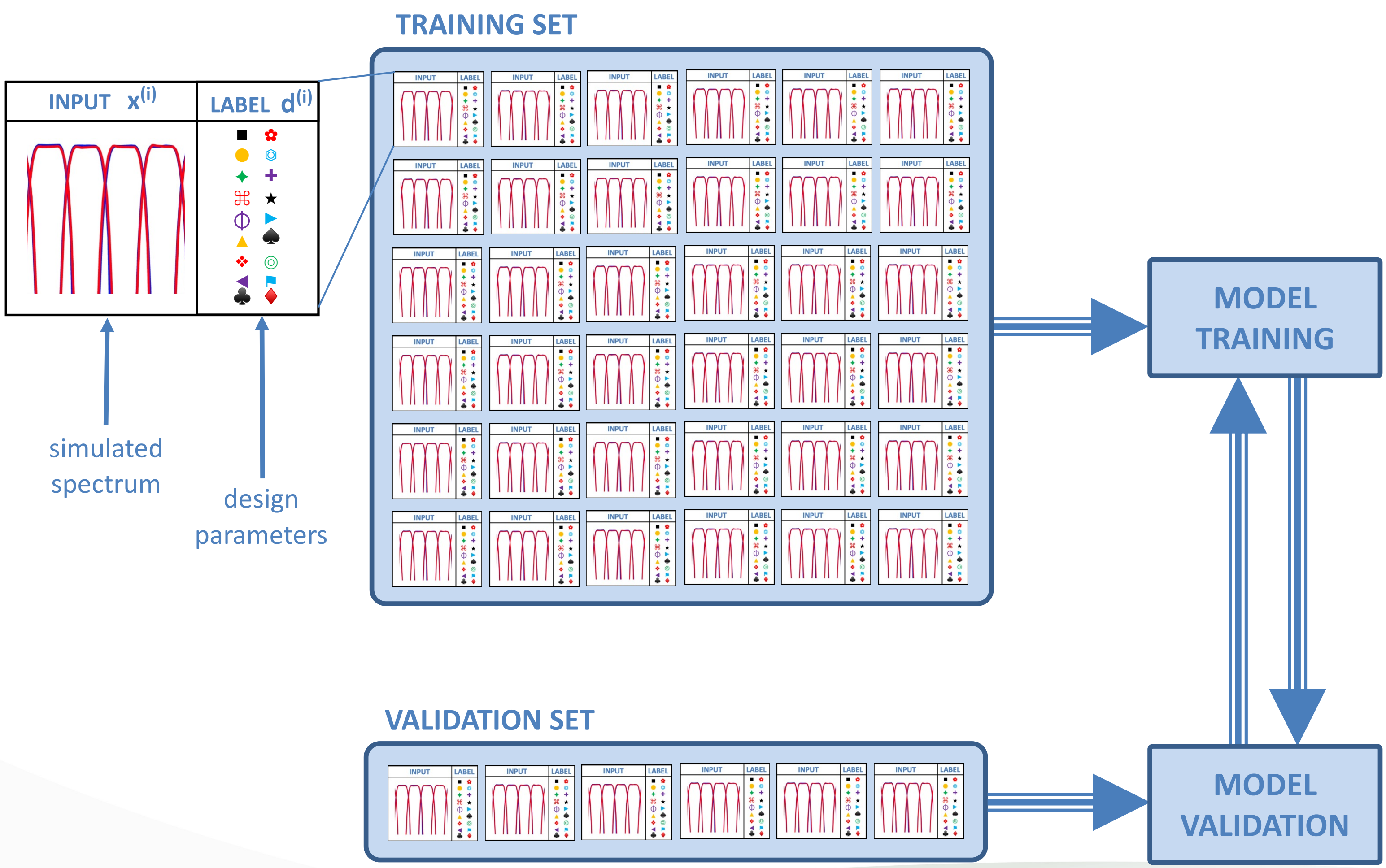
- Process uniformity and consistency is critical in the manufacturing of photonic chips.
- Traditionally, standard statistical methods are used to compensate for systematic process non-uniformities:



systematic index variation

Design Optimizations

Adjustments of design parameters through ML



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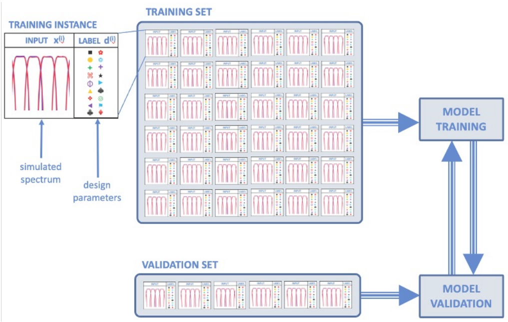

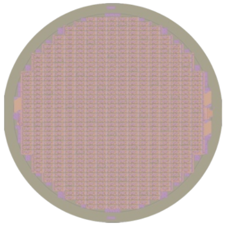

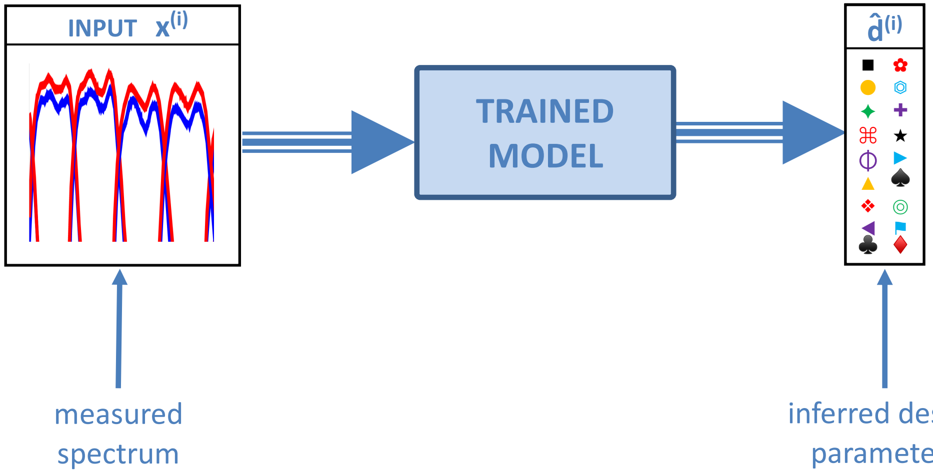

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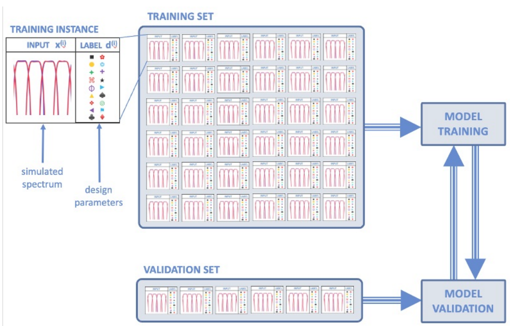
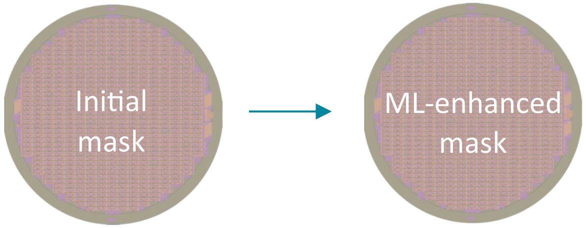
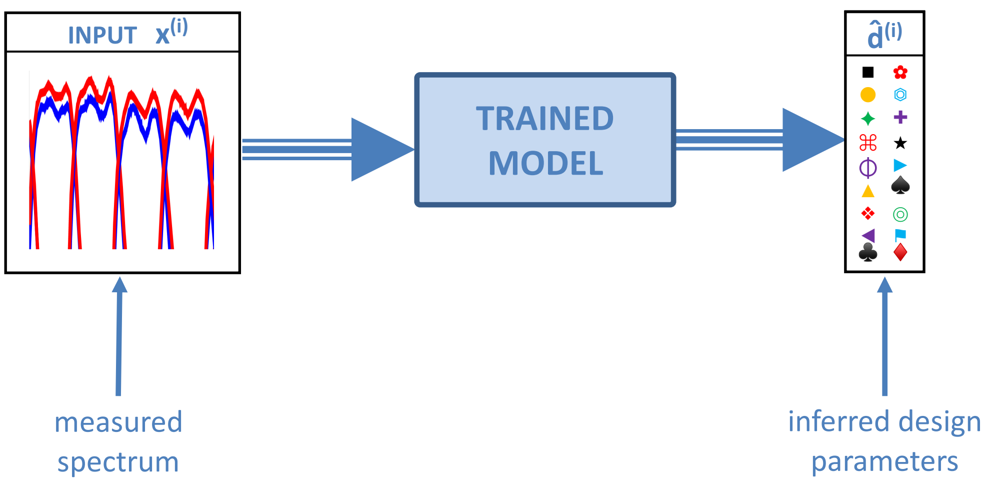


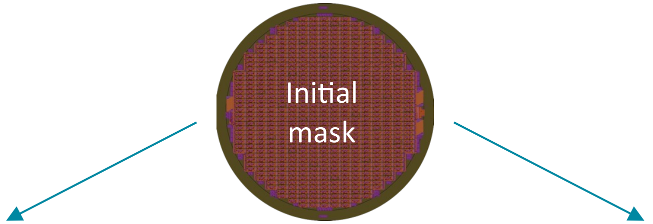


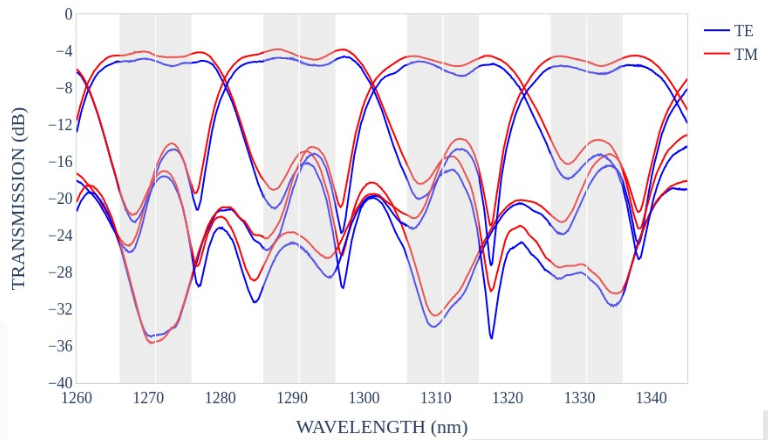


Design Optimizations

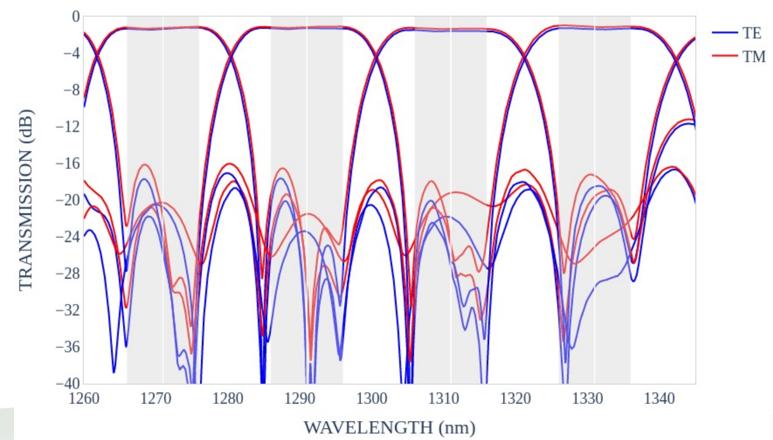
Adjustments of design parameters through ML

- To validate the approach, we applied it to a production mask with 600 devices:
  - Devices on the mask were designed to be identical, except for a refractive index distribution correction computed by traditional statistical means.
  - Despite the built-in compensation for systematic refractive index variations, nominally identical devices showed significant variations in performance stemming from process variabilities:





A poor-performing chip

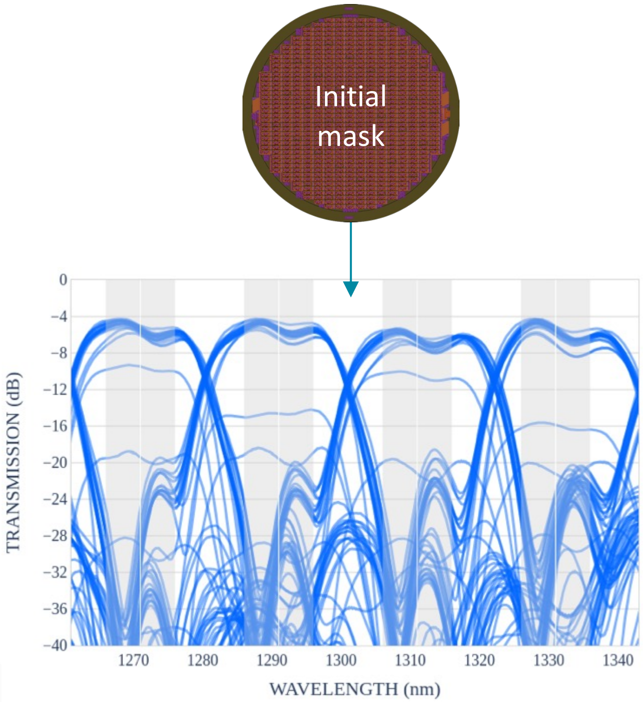


A high-performing chip from the same wafer

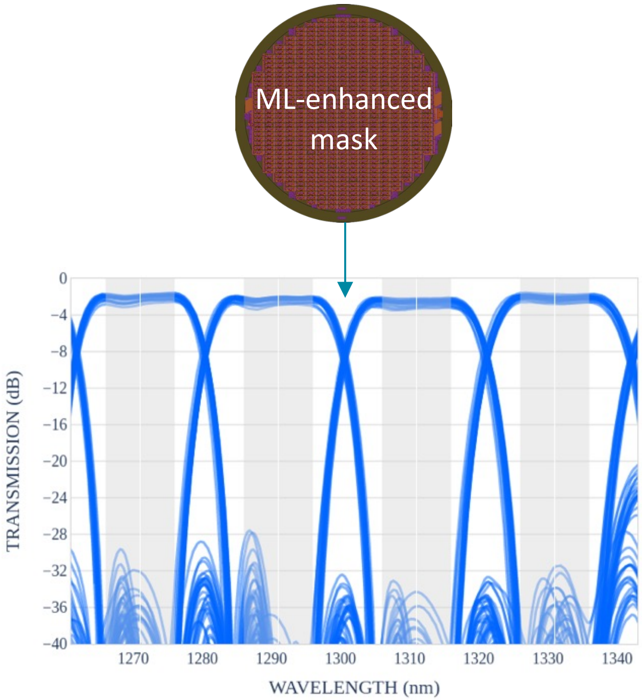
Design Optimizations

Adjustments of design parameters through ML

- To validate the approach, we applied it to a production mask with 600 devices:
  - We used the model predictions to insert corrections into each of the chips on the mask, thereby producing a ML-enhanced version of the production mask.



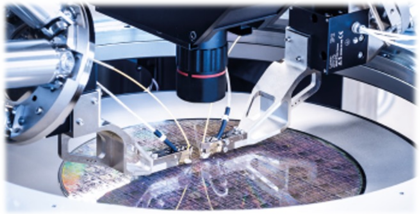
20 worst performing chips in the initial version of the mask.



The same 20 chips in the ML-enhanced version of the mask.

Performance Predictions

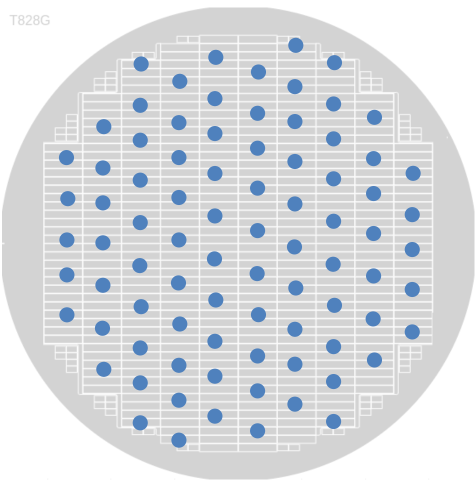
Classification based on a wafer probe measurement



Performance Predictions

Classification based on a wafer probe measurement

Enablence



Probed locations
on the wafer

Performance Predictions

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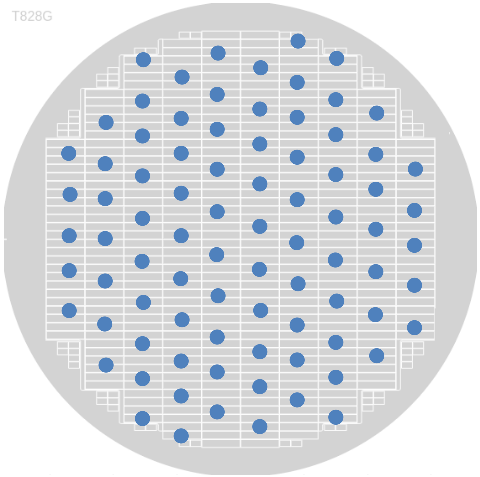

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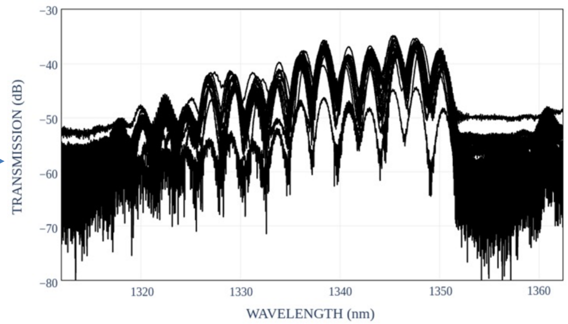

Typical spectroscopic
signature

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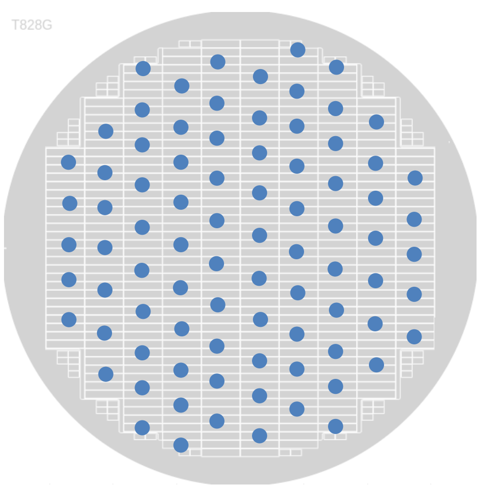

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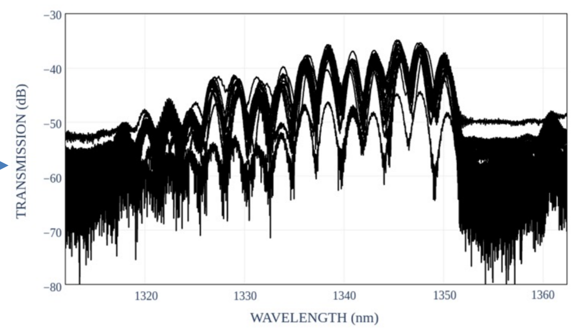

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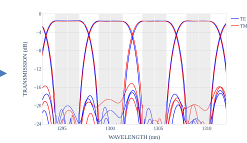

Predicted performance of
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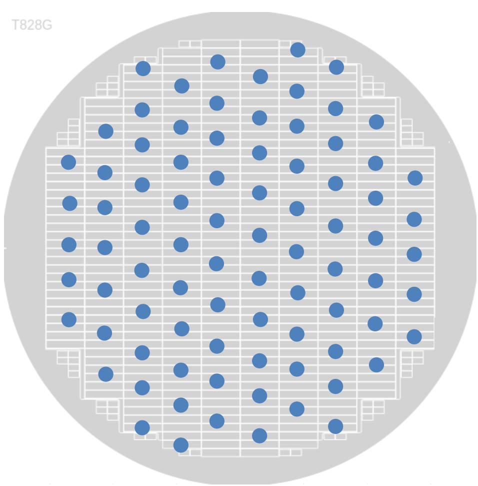

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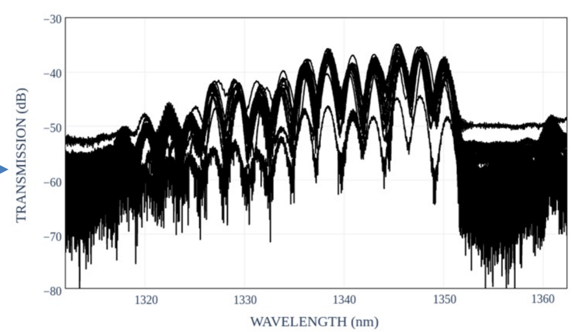

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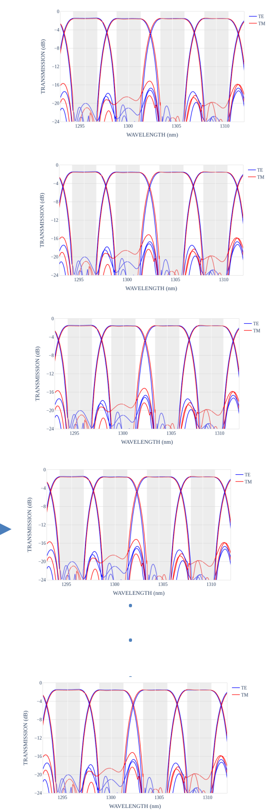

Specification parameters:

1. IL
2. IL uniformity
3. Grid detuning
4. Channel spacing uniformity
5. 0.5 dB passband
6. 1 dB passband
7. 3 dB passband
8. PDL
9. Ripple
10. Adjacent crosstalk
11. Non-adjacent crosstalk
12. Total crosstalk

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Predicted performance of hundreds of chips on a wafer

Performance Predictions

Classification based on a wafer probe measurement

Traditional chip testing

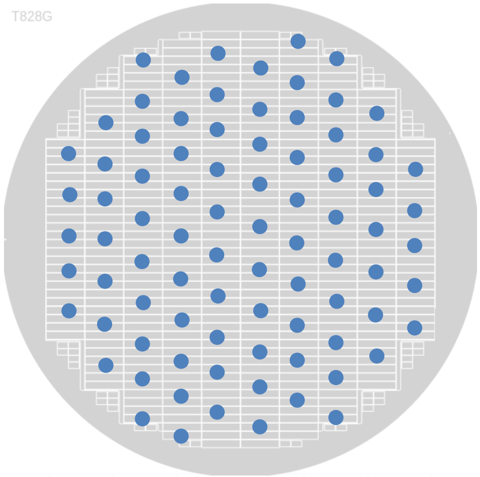
Time to measure a 4-channel chip	2 minutes
Cost of measuring a 4-channel chip (North America)	$4.25
Cost of measuring a 4-channel chip (Asia)	$0.55
Cost of characterizing a wafer with 600 chips	$2550 / $330
Time to measure a wafer with 600 chips	20 hours

Wafer probe testing

Time to perform a wafer probe measurement	12 minutes
Time to infer the PASS/FAIL of all chips on a wafer	instantaneous
Effective measurement time per chip	1.2 seconds
Cost of characterizing a wafer with 600 chips	$25
Time to measure a wafer with 600 chips	12 minutes

Performance Predictions

Classification based on a wafer probe measurement



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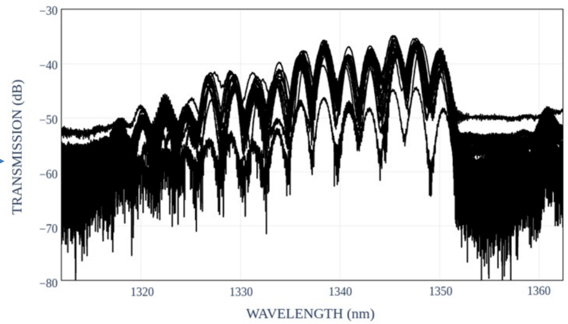

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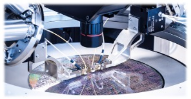

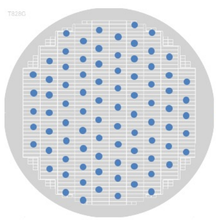

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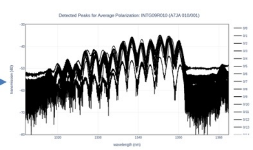

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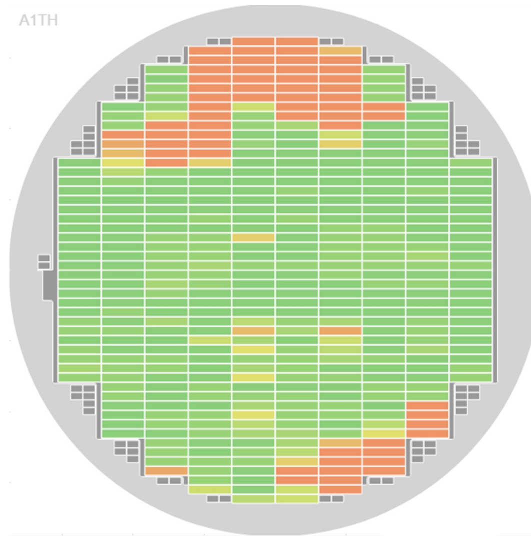

Predicted PASS/FAIL
over 26 specification
parameters

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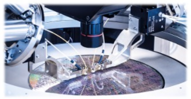

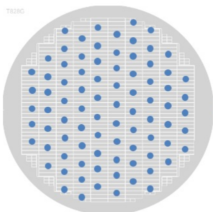

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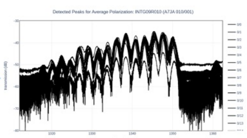

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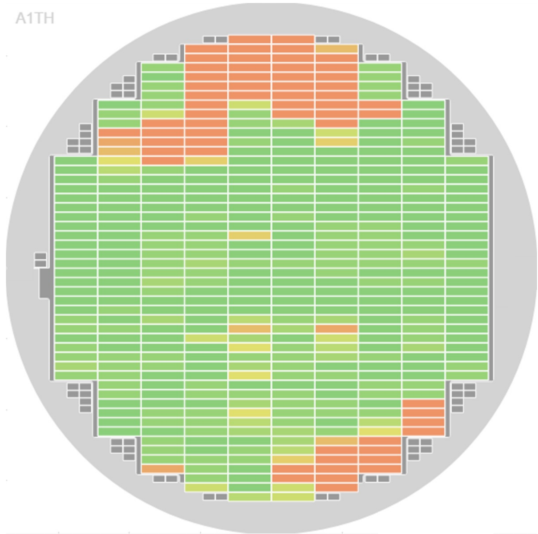

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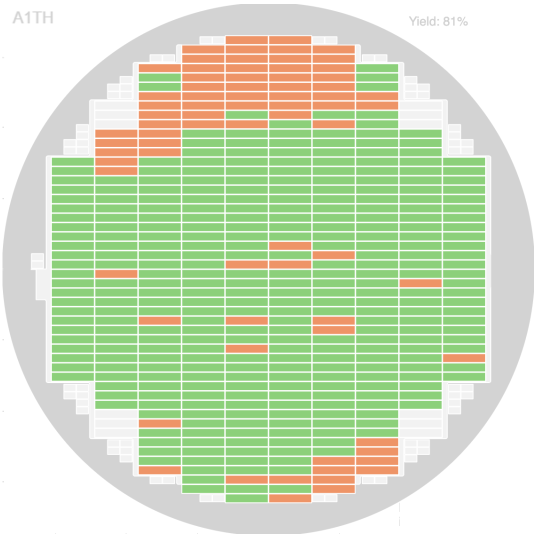

Actual PASS/FAIL

over 26 specification parameters

Optimizations Through ML

Robust designs for volume manufacturing

Enablence

- AI/ML has become instrumental in our work in extending the reach of the photonics technology.
- We continue using “human-machine collaboration” to achieve outstanding uniformity of performance of mass-produced photonics chips despite our imperfect control of the fabrication process.
- The ability of ML to find correlations within weak and noisy signals gives us an unprecedented control over our process, making in-situ monitoring of optical wafer fabrication and real-time process adjustments possible.
- Our current work focuses on the use ML algorithms to scale the capabilities of our platform to integrated optics solutions in LiDAR and OCT applications.

Conclusions

Enablence

- Machine learning has the capacity to capture features from vast amounts of high-dimensional data.
- We described how AI/ML was used in the field of photonic integrated circuit design and manufacturing:
  - We used deep neural network multivariate regression model to optimize the individual design parameters of hundreds of devices on a mask.
  - We used a support vector machine (SVM) to predict the performance of optical chips in multi-dimensional space.
- These approaches bring the power of ML to both the design of optical chips and their manufacturing, demonstrating the tremendous potential of AI/ML for increasing the scale and reach of the photonics industry.

Enablence

Custom Optical Design

We have built systems-on-a-chip for avionics, medical robotics, automotive LIDAR, 3D mapping, and optical sensing. We can do commercial-grade prototyping or high-volume production of chips. Our mechanical design engineers can also assist with fiber pigtailing and packaging. Through PLC, we can help our customers to open new market opportunities.

Inquire

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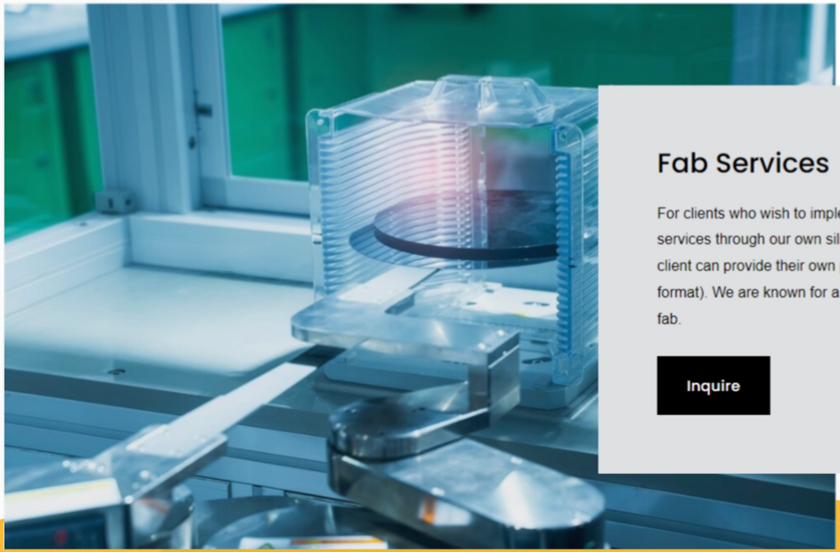

Fab Services

For clients who wish to implement their own PLC designs, we offer services through our own silica-on-silicon PLC fabrication facility. The client can provide their own photomask, or digital mask data (GDS format). We are known for a quick turnaround from our well-equipped fab.

Inquire