Deep Learning Enabled Nanophotonic Design Via Finite Element Simulation

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INTRODUCTION:

- The designing of Metamaterials (MMs) and Metasurfaces (MSs) for exotic functionalities and desired optical response requires iterative computational simulations. Hence the inverse design formulations based on deep neural networks[1] are more useful for structural designing with desired optical response from MS structure.
- Here we propose a data driven approach, conditional Generative Adversarial Network(cGAN)-a deep learning model, for inverse designing of a MS based Half-waveplate[2] (Fig. 1a) and extend it to chiral beam splitter(Fig. 1b) demonstrating the Photonic Spin Hall Effect(PSHE) [3].
- The cGAN[4] could capture and understand the intrinsic complex relationship between nanoantenna design and its spectral response and generate new structures for user-defined spectra.

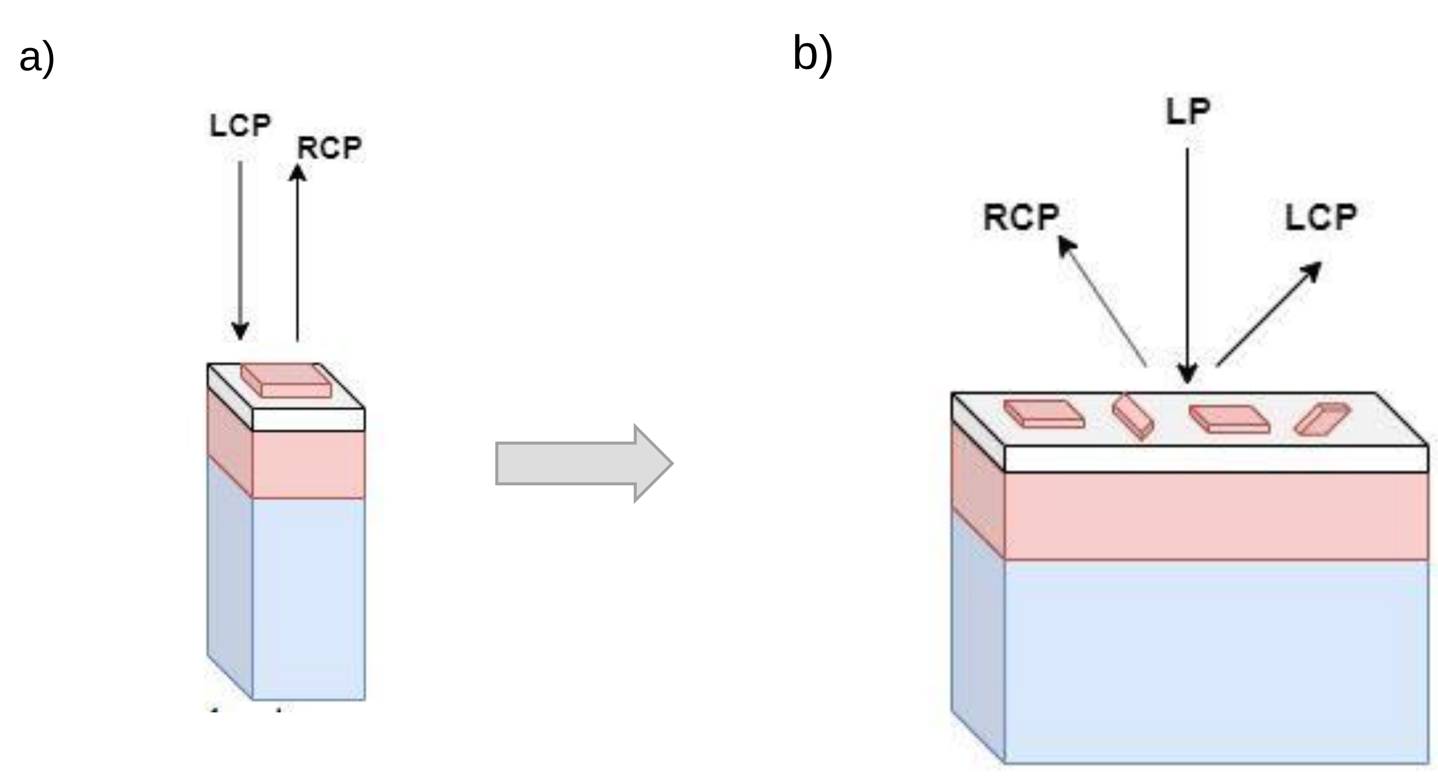

Figure 1. Schematic of a) MS based Half-waveplate nanoantenna. b) An array of nanoantenna for demonstrating PSHE-splitting of linearly polarized light into two circular polarization .

COMPUTATIONAL METHODS:

COMSOL MULTIPHYSICS®- RF Module.

- Al-nanoantenna (NA) of 50nm thickness on 50nm SiO_2 spacer deposited on 150nm Al-mirror on a Si-substrate. The simulation yields reflection spectra for LCP to RCP conversion in 300nm-1000nm wavelength range(Fig. 2c).
- Geometric dataset generation for different structural design like Arc, Rectangle and Double arc (Fig. 3) with random parameters is obtained using COMSOL Multiphysics® via LiveLink™ for MATLAB® using a random parameter generation algorithm.
- The SiO_2 spacer thickness effecting the spectral response due to gap-plasmon coupling and dispersion is considered as a design parameter in GAN and included as a color label into the image(Fig. 2c). Grey color label corresponds to thick spacer. Different shades of grey in image (Fig. 3) depicts different spacer thickness.

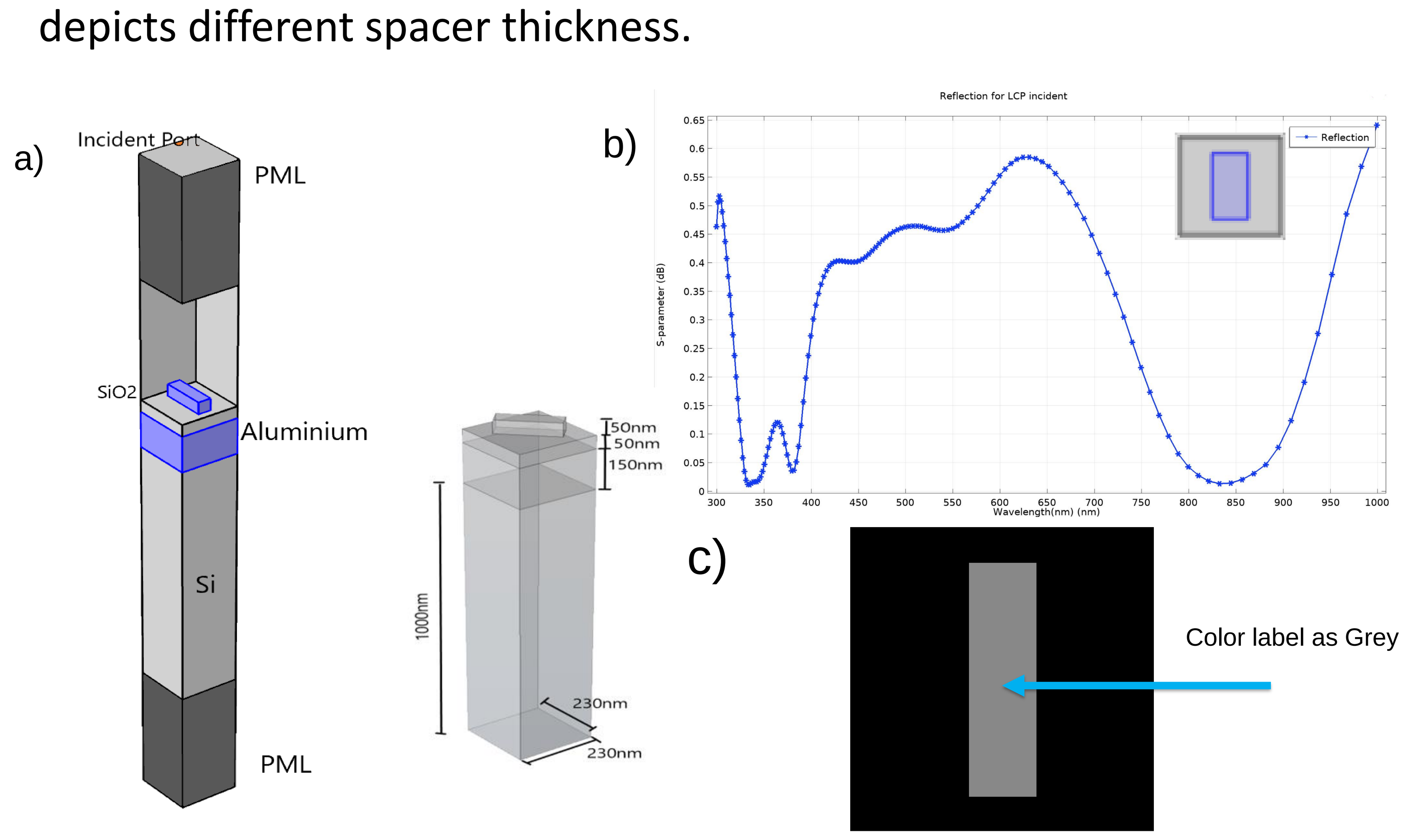

Figure 2. A dataset sample for deep learning model. Each dataset is b) a LCP to RCP conversion reflection spectrum and c) its corresponding cross-sectional structural design.

- Generated dataset consists of 1000 Half-waveplate images of 45x45 pixels (Fig. 3) and corresponding reflection spectrum as a 100 point vector.

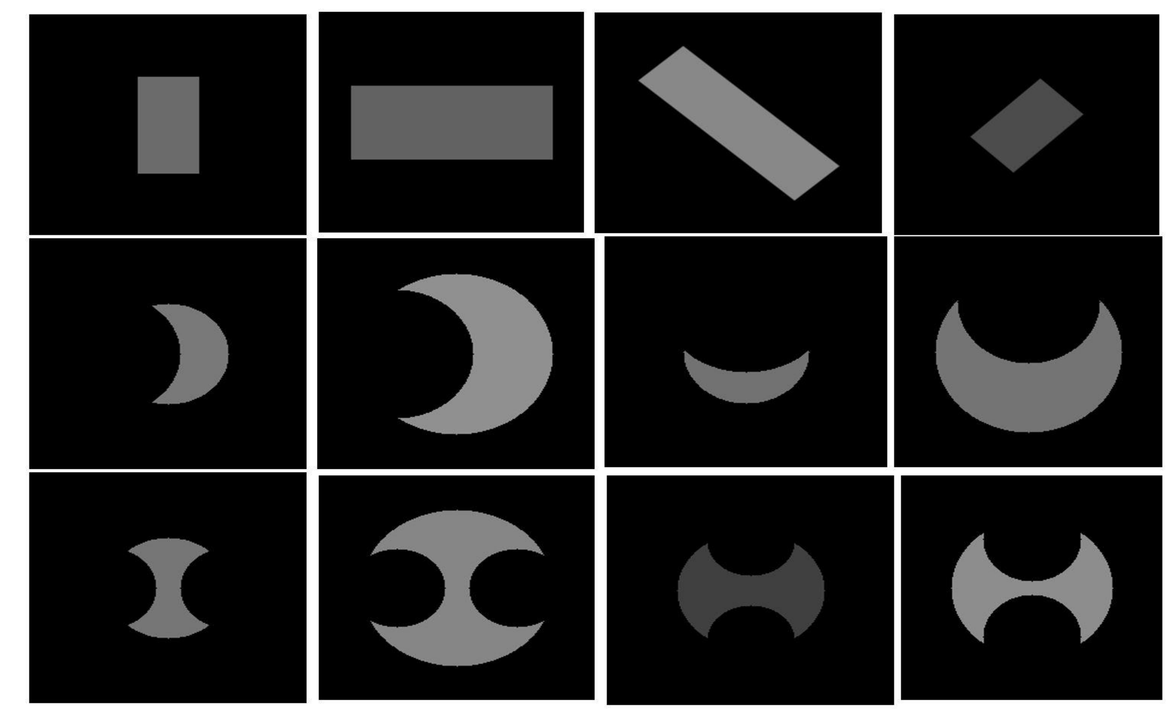

Figure 3. Half-Waveplate samples in training dataset.

DEEP LEARNING MODEL- cGAN

- cGAN is conditional with desired optical response (Fig.4). The two networks, Generator and Discriminator plays minmax game.
- Generator learns to generate new designs of MS based Half-waveplate structure.
- Discriminator learns to classify the real and fake MS Half-waveplate designs.
- At equilibrium, cGAN network successfully generates new designs for desired optical response.

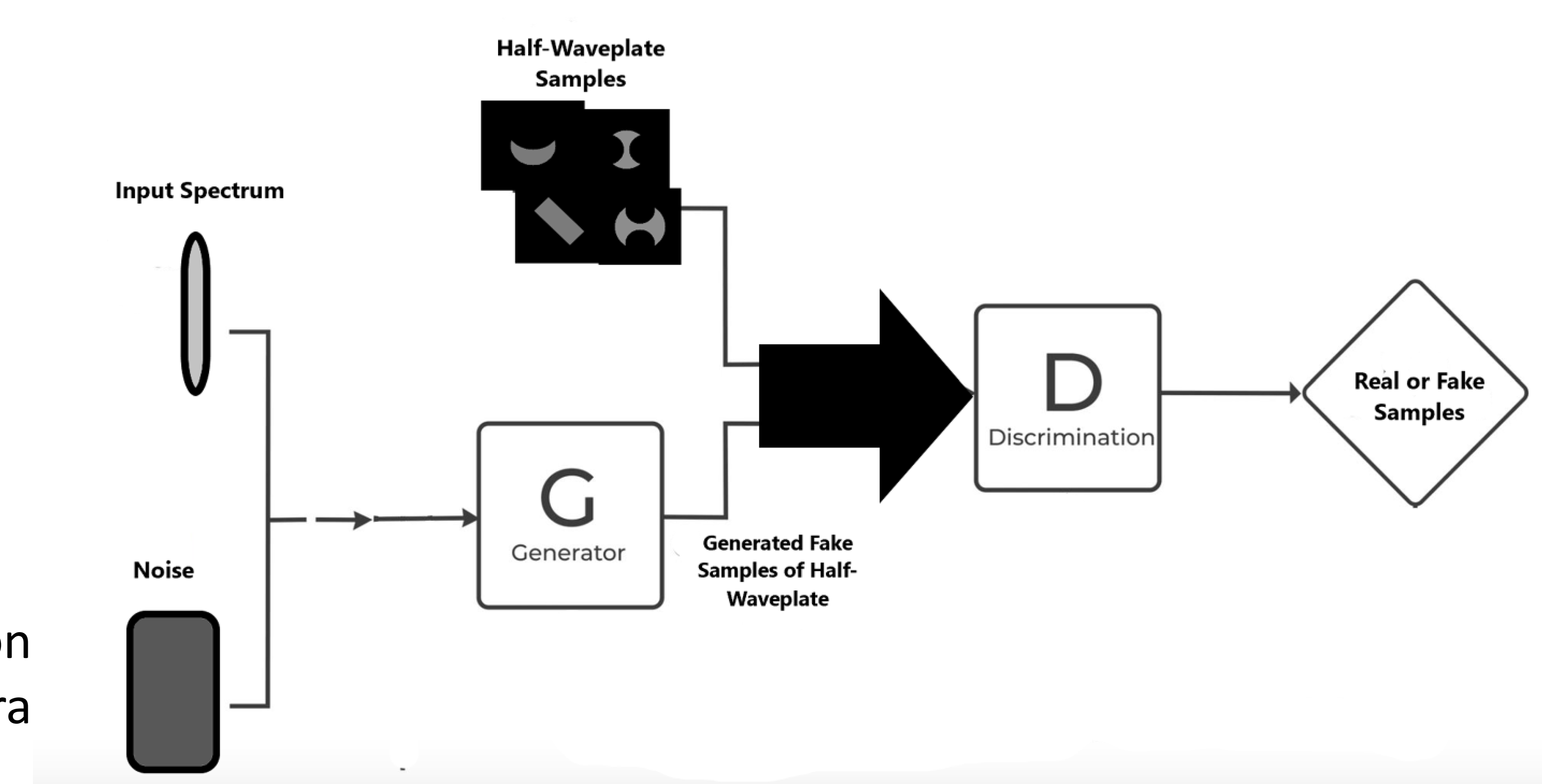

Figure 4. Schematic for cGAN for generating new Half-waveplate design for desired optical response.

DISCUSSION:

- Deep learning assisted inverse designing explores new design parameter space with less computational cost.
- Design flexibility and functionality like Half-waveplate, PSHE, etc. in MSs design using deep learning methods eradicates need of iterative computations.
- On-demand designing of MMs and MSs for sensing driven properties based on deep learning models could give mobility in broadband ranges.

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