# Prediction of Optical Waveguide Parameters Using CNN – Final Report

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**Abstract**

**This project aims at building connection between field patterns and the geometrical dimensions of optical waveguides. In the research part, it illustrates the process of field pattern prediction. In the experiment part, it shows the CNN model to predict the dimensions of waveguides. According to the convolutional property of CNN, it is created by assuming the field values as inputs, and the geometrical dimensions of the waveguide as outputs. Results show that the prediction can approximate the ground truth in a short time compared with traditional methods.**

## I. Introduction and Motivation

Electromagnetic waves can travel along waveguides using different mode, which are TE (Transversal Electric) and TM (Transversal magnetic). Generally, we use dimensions (width and height) of waveguide to judge its mode. It is common to think about reversing it: using pattern modes to predict the dimensions of waveguide, so that it can be used in some precision instruments for detecting.

But physical fields are tensor quantities which vary in time and/or space axes. They are very common in our daily life, such as temperature field, gravitational field, electromagnetic field. It's essential to understand the distribution of field patterns in scientific research and engineering problem for accurate predictions of relative phenomena as well as the development of related devices. Therefore, I want to do research on this topic.

I learnt deep learning structure design from the reference papers and books [1-3], and apply the theories I learnt from class. The traditional method to obtain the field pattern is to solve field equations that contain the information of a specific field. For example, for electromagnetic field patterns, one needs to solve Maxwell equations of electrodynamics. This method costs a lot of computational resources as field equations have the form of multivariable and partial differential equations.

In this paper, I found a potential method to get the field patterns and predict parameters, which can save much time and computation.

## II. Related Literature

Generally, there are two topics in optics, one is "optics for AI" and the other is "AI for optics". The second theme is more related to my current work. In "Deep Learning Book", it illustrates what convolution is, and explains the motivation behind using convolution in a neural network. It introduces basic knowledge of CNN, such as how convolution can be applied to many kinds of data with different numbers of dimensions, which constructs a foundation of my current model.

In paper "Leveraging AI in Photonics and Beyond"[4], Gandhi Alagappan and other researchers illustrates In a celestial manner, the behavior of electromagnetic waves corresponding to this entire spectrum can be succinctly described by the golden set of Maxwell equations. The entire cycle of design, modeling, and simulation carried by soft computing algorithms will accelerate execution speeds by two to three orders of magnitude. They analyzed the number of the publication with topics including AI and photonics from web of science is searched by conditions: AI (topic) or deep learning (topic) or machine learning topic and photonics (topic) from 1996 to 2021.

In another paper of Gandhi Alagappan called "Prediction of electromagnetic field patterns of optical waveguide using neural network"[5], the authors used RNN and FNN architectures to predict mode pattern

for an optical waveguide with width and height. The paper shows how field patterns can be predicted by employing artificial neural networks. The FNN and RNN models are trained using a set of simulated datasets, obtained by solving the Maxwell's equation.
From these papers, I got a connection between electromagnetic field patterns and neural networks.

## III. PRELIMINARIES

### 3.1 Optical waveguide

The optical waveguide is a channel which can guide electromagnetic waves. It is the most fundamental device in modern optical system. Some complicated optical devices, like optical resonators and couplers, are built from optical waveguides. The waveguide consists of two parts: core and cladding. Those two parts are made of dielectric materials and have different refractive index. The core refractive index is greater than the cladding refractive index so light can be confined in the core and propagate along the waveguide. Figure 1 is a schematic of a rectangular waveguide. [6]

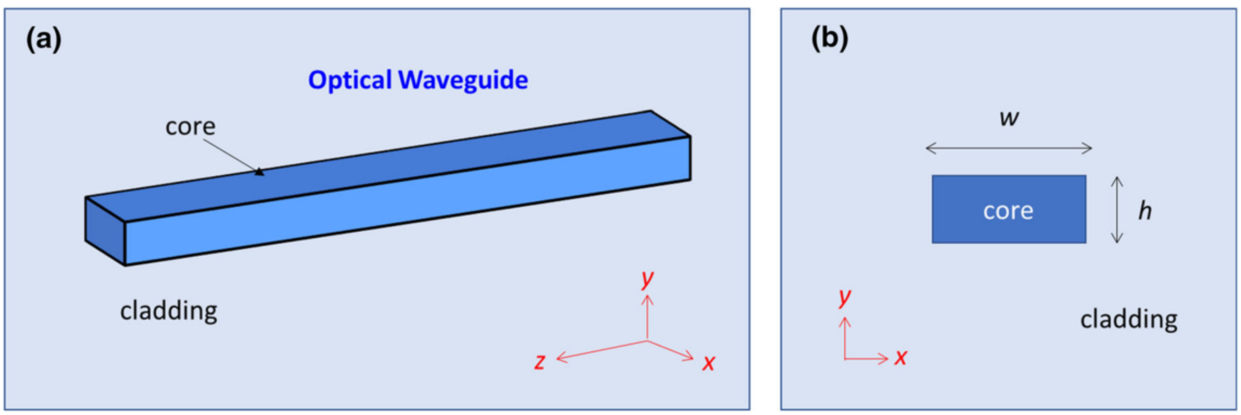


*Figure 1: (a) Schematic of the optical waveguide. (b) Schematic of the waveguide cross section*

### 3.2 Electromagnetic field patterns

The electromagnetic field consists of magnetic field and electric field. The electromagnetic field pattern has transverse electric (TE) mode and transverse magnetic (TM) mode, which are classified based on the dominant component in the pattern. The mode pattern plays an important role in investigating behaviors of optical waveguides. One can solve the eigenvector of the time independent Maxwell's equation to get the electric field pattern E in the equation. [4]

$$\nabla \times \nabla \times \mathrm{E} - \frac{\omega^2}{c^2} n^2(x, y)\mathrm{E} = 0$$

where ω is the angular frequency, c is the speed of light and n(x, y) is the refractive index of the optical waveguide in the xy-plane. After that, the magnetic field pattern H can be obtained by using the following equation. [4]

$$H = (i/\omega\mu_0)\nabla \times \mathrm{E}$$

## IV. Approach

### 4.1 First turn – prediction of field patterns

In order to create the connection between field patterns and geometrical dimensions of waveguides, it is a must to learn about field pattern first. A good way is to understand it through its prediction. Therefore, in the first turn, the input data should be geometrical dimensions of waveguides and the output data should be field patterns. I started analyzing from a clearer part, that is predicting the field patterns using RNN.
The magnetic field pattern can be obtained by using the same model (an interchange of the width and height of the optical waveguide) because of the symmetry property of the optical waveguide. When considering electromagnetic field patterns, we only need to consider the dominant component of the field pattern.

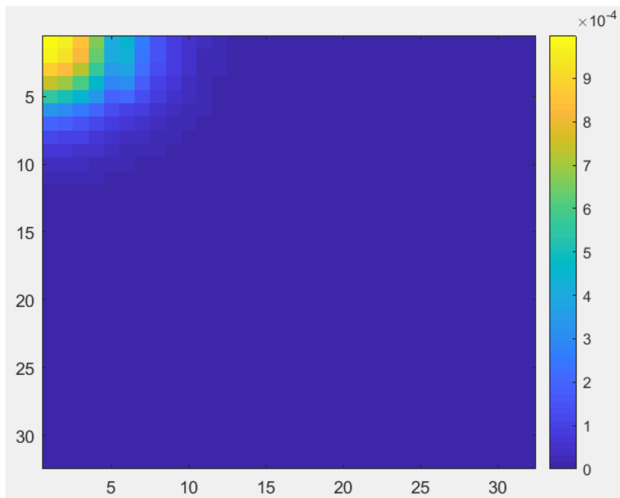


*Figure 2: The electric field pattern of an optical waveguide with w = 1.2 , h = 1.2 and $n_c$ = 1.5*

Figure 2 is the electric field pattern of an optical waveguide with w = 1.2 , h = 1.2 and nc = 1.5 (the refractive index of the core). The input dataset consists of geometrical parameters of the optical waveguide: width of the waveguide w and height of the waveguide h. The output dataset is obtained by taking one-quarter of the field pattern, like Figure 3, and discretizing the pattern into 1024 tiny pixels denoted as Fi where i = 1, 2. . . , 1024.

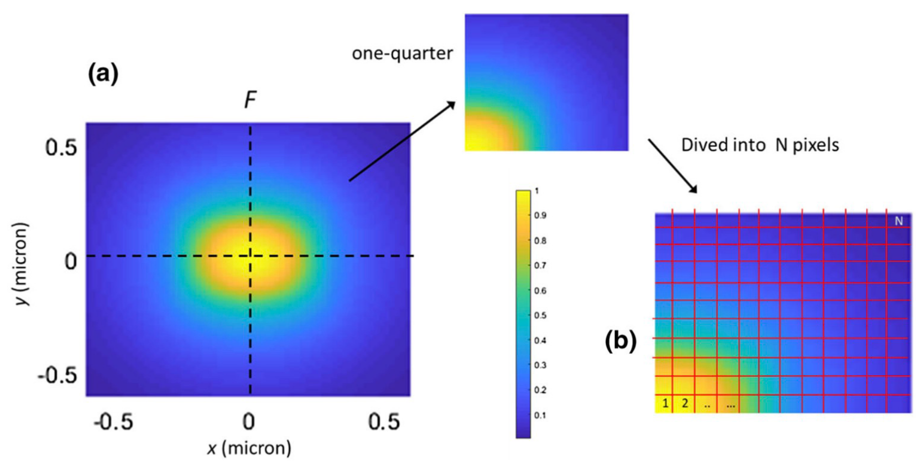


*Figure 3: (a) an electric field as a function of x and y. (b)One quarter of the field pattern is discretized into N tiny pixels denoted as $F_i$ where i = 1, 2. . . ,N*

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In this project, w varies from 0.1 to 1.2 and h varies from 0.1 to 1.2. There are 2500 samples, so I divide the dataset into 3 parts: training data, testing data and validation data, with 1600 samples, 500 samples and 400 samples, respectively. The reference paper[9] lists top 15 layouts (with different number of neurons and layers). I choose the layout with the best performance: 3 RNN hidden layers with 64, 96, and 224 neurons in each layer and 1 output layer with 1024 neurons. I use Keras to build my RNN model. Figure 4 is the model summary. In Keras [7], the SimpleRNN layer is a fully connected RNN layer and the Dense layer is a fully connected layer. The SimpleRNN layer accepts 3-dimension data and outputs 2-dimension or 3-dimension results. Since we only have 2D input, this means that we need to reshape 2D input into 3D for the first layer.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
simple_rnn_9 (SimpleRNN)     (None, 2, 64)             4224

simple_rnn_10 (SimpleRNN)    (None, 2, 96)             15456

simple_rnn_11 (SimpleRNN)    (None, 224)               71904

dense_3 (Dense)              (None, 1024)              230400

=================================================================
Total params: 321,984
Trainable params: 321,984
Non-trainable params: 0
_________________________________________________________________
```

*Figure 4: RNN model summary*

For this model, I choose mean squared error as the loss function, RMSprop as the optimizer, batch size = 10 and epochs = 2000.

### 4.2 Second turn – prediction of geometrical dimensions

I chose Convolutional Neural Network to predict electromagnetic field patterns. We can recognize the pattern from a view of smaller area, thus we have receptive field. With the combination of receptive field and parameter sharing, we call it convolutional layer. Fully connected layer can be used in many situations, but it might not do that well in specific problems. Like CNN, it has a larger model bias, it might not a bad thing. Because CNN is specialized in dealing with pictures because of it contains some characteristics of figures. That’s what we say each performs his own function. Therefore, I will make the electric field patterns figures as my input (Figure 5 the original dataset), let width and height of waveguide as my output.

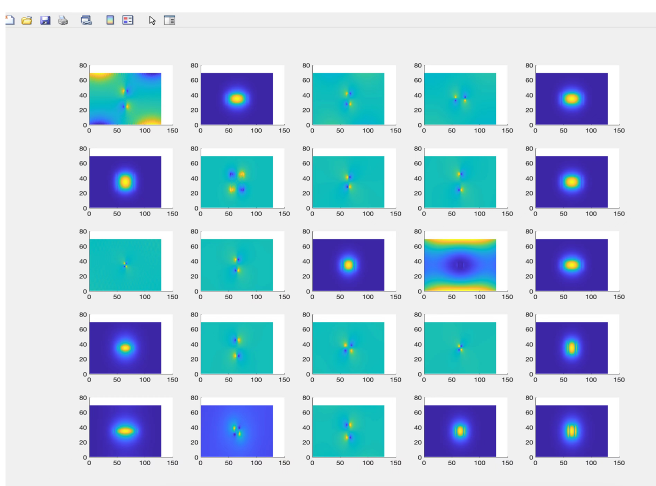


*Figure 5: Input – Electric field patterns*

The input layer reads in a regularized (uniformly sized) image. Each neuron in each layer takes as input a small set of local nearest neighbors from the previous layer, i.e. the local perceptual field and weights are shared, and the neuron extracts some basic visual features, such as edges, corner points, etc., which are later used by higher level neurons. Convolutional neural networks obtain feature maps by convolutional operations, and at each location, units from different feature maps get their own different types of features. A convolutional layer usually contains multiple feature maps with different weight vectors, allowing a richer feature set of the image to be retained. The convolution layer is followed by a pooling layer for down sampling, which reduces the resolution of the image and the number of parameters on the one hand and obtains robustness for translation and deformation on the other. The alternating distribution of convolution and pooling layers results in a bipyramidal structure with a progressively larger number of feature maps and a progressively lower resolution. The following is my CNN model for predicting field patterns.(figure 6)

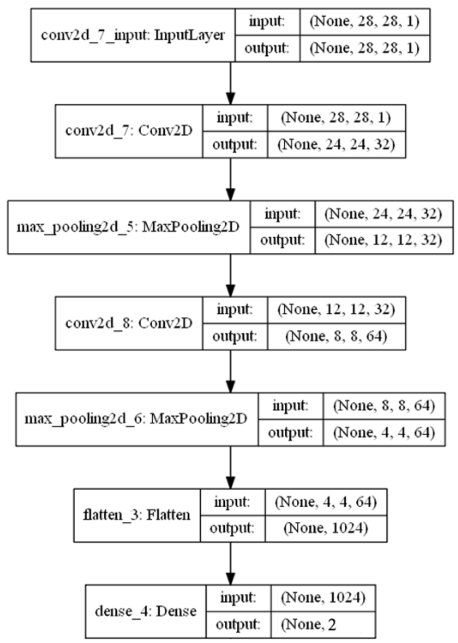



*Figure 6: CNN model*

## V. EXPERIMENT

### 5.1 Code implementation

1) Load the dataset from .mat file
2) Data preprocessing:
    - Shuffle all the data
    - Reshape the input data from 2D to 3D
3) Build the RNN
4) Compile the RNN
5) Train the model
6) Evaluate the model
7) Comparison between the ground truth and prediction

For this model, I choose mean squared error as the loss function, and Adam as my optimizer, batch size = 32 and epochs = 500. Following is the input (figure 7) of the model.

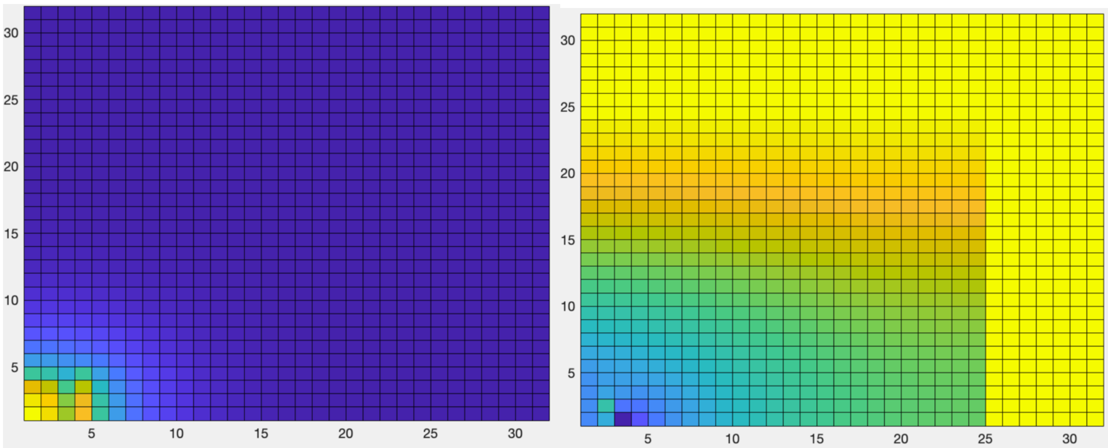
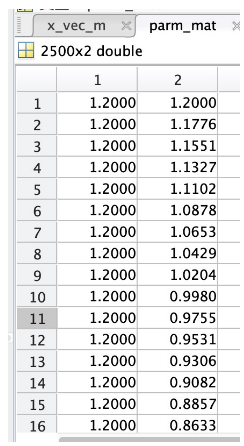



*Figure 7: (a) Ex{100} Figure of Input (b) Ex{2000} Figure of Input*

The output data figures can be seen through matplotlib. I use parm_mat as my output. (Figure 8)


x_vec_m | parm_mat
2500x2 double

| | 1 | 2 |
|---|---|---|
| 1 | 1.2000 | 1.2000 |
| 2 | 1.2000 | 1.1776 |
| 3 | 1.2000 | 1.1551 |
| 4 | 1.2000 | 1.1327 |
| 5 | 1.2000 | 1.1102 |
| 6 | 1.2000 | 1.0878 |
| 7 | 1.2000 | 1.0653 |
| 8 | 1.2000 | 1.0429 |
| 9 | 1.2000 | 1.0204 |
| 10 | 1.2000 | 0.9980 |
| 11 | 1.2000 | 0.9755 |
| 12 | 1.2000 | 0.9531 |
| 13 | 1.2000 | 0.9306 |
| 14 | 1.2000 | 0.9082 |
| 15 | 1.2000 | 0.8857 |
| 16 | 1.2000 | 0.8633 |

*Figure 8: parm_mat dataset, where 1st column is w and 2nd column is h*

The input dataset is obtained by taking one quarter of the field pattern and discretizing the pattern into tiny pixels. The output dataset consists of geometrical parameters of the optical waveguide: width of the waveguide w and height of the waveguide h. w varies from 0.1 to 1.2 and same as h.

There are 2500 samples, so I divide the dataset into 3 parts: training data, testing data and validation data, with 1600 samples, 500 samples and 400 samples, respectively.

After fully understanding the field pattern and the parameters, I build CNN model and consider it by inversing the output and the input. The cross section of the optical waveguide is discretized into a set of pixels, which contains the field values. I used pooling after convolution, like two convolutions and one pooling. After that, I straighten the matrix that we get into a vector. Putting vectors in fully connected layer and using softmax. Finally, we can get the output. For this model, I choose mean squared error as the loss function, and Adam as my optimizer, batch size = 32 and epochs = 500.

**5.2 Evaluation**

Using mean squared error (MSE) to evaluate the exact result and the predicted one. MSE measures the amount of error in statistical models. It assesses the average squared difference between the observed and predicted values. When a model has no error, the MSE equals zero. As model error increases, its value increases.

In regression, the mean squared error represents the average squared residual. As the data points fall closer to the regression line, the model has less error, decreasing the MSE. A model with less error produces more precise predictions.

## VI. RESULT

Figure 9 is the training loss of RNN model.

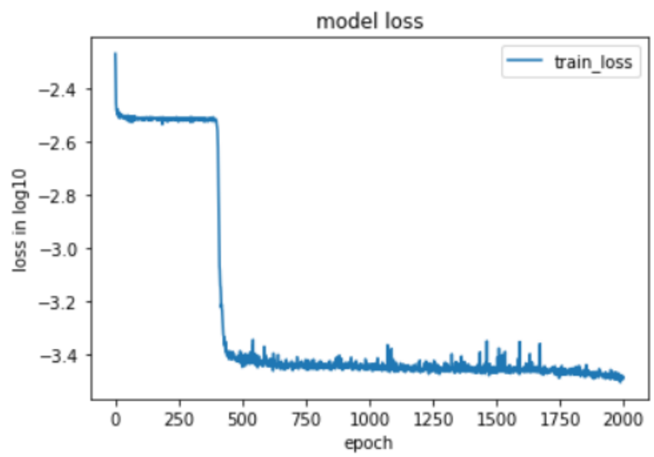



*Figure 9: Training loss*

Here are four prediction results from the test dataset. In figure 10, it should be noted that color bars between the prediction and the ground truth are not identical, so the model still could be improved in the future. The L2-norm of figure 10 (left) and figure 10 (right) is 0.02620 and 0.00792, respectively.

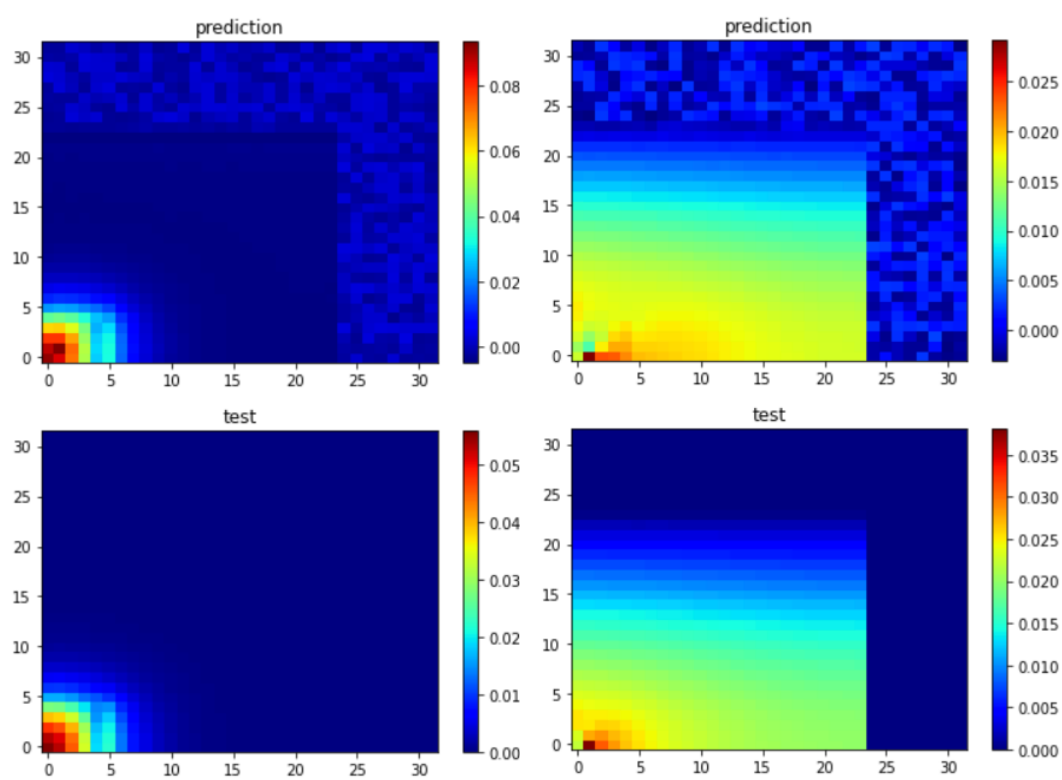



*Figure 10: Results*

Figure 11 is the training loss of the CNN model.

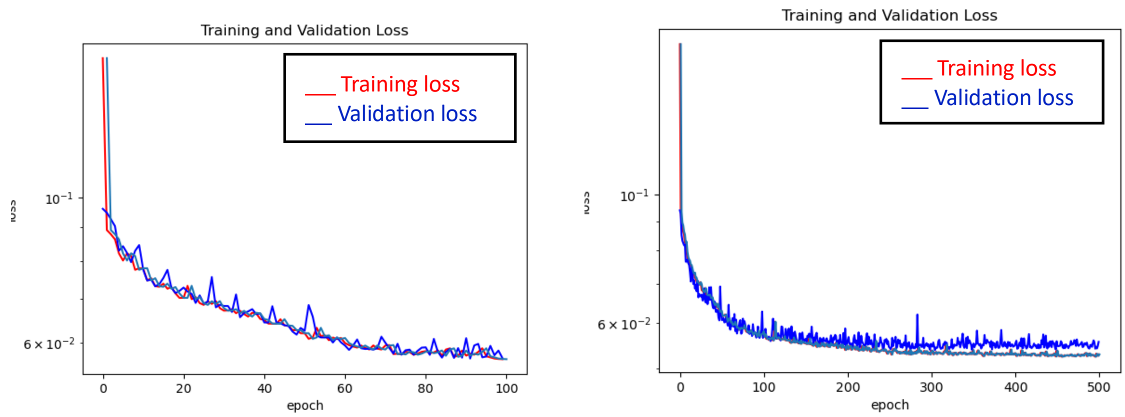



*Figure 11: (a)Training and validation loss curve (epoch 100) (b)Training and Validation loss curve (epoch = 500)*

These results show my analysis on field patterns prediction by RNN, and the experiment of prediction on waveguide parameters by Convolutional neural networks. Y scale is set at log value. We can see from left figure, no changes show before 450 epochs, but there is a huge drop around epoch 480, and after that the loss tends to be gentle. In the right figure, the training loss and the validation loss seems to be similar, and both have a gentle fall.

Here is the prediction result from the test dataset. The MSE score of the width and height is 0.0559. (figure 12)

```
In[3]: model.predict(testInput)
Out[3]:
array([[0.557686  , 0.5913815 ],
       [0.42939582, 0.62133825],
       [0.41590282, 0.7161096 ],
       [0.6394433 , 0.70133626],
       [1.0420992 , 0.6344788 ]], dtype=float32)
```

*Figure 12: Prediction result of CNN model*

## VII. Conclusion

This project shows that geometrical dimensions of waveguides can be predicted by CNN and the field patterns can be predicted by RNN. The field pattern of optical waveguides is the electric field pattern. The field pattern is discretized into 1024 pixels as output and the input is the geometrical parameters of the optical waveguide (width and height) in RNN model. The output is parameters of waveguides, and the input is field patterns in CNN model. The data for training and testing is obtained by using finite differences method [9]. The network architecture is based on the reference [8]. With these two models, I have built a connection between field pattern and parameters of waveguide, which can be applied to different optical areas and devices. The future work will focus on enhancing the performance of the CNN prediction by increasing the complexity of the network, such as increasing the number of neurons and layers, prediction on integration of 2 inputs and applying other deep learning algorithms on prediction.

## VIII. Challenges

*A.* Pre-process the dataset. The original dataset is a rectangle figure with a size of 129*69, which needs to be pre-processed.

*B.* Undersdand the input: field patterns.

*C.* Create bidirectional of prediction, which is using field patterns to predict geometrical dimensions of waveguide and using dimensions to predict field patterns.

## IX. Project Schedule

Phase 1: 20 Oct – 10 Nov: Search information and document of the project, prepare the proposal and the slides of the project. Pre-processing datasets.
Phase 2: 15 Nov – 25 Nov: Build the model and adjust it.
Phase 3: 30 Nov – 11 Dec: Finish the presentation slide.
Phase 4: 14 Dec – 19 Dec: Finish final report.

## X. Reference


*1) Chapter 9, 9.1-9.3 of Deep Learning Book*

*2) Procedia Computer Science 132(2018)377-384 "An Analysis Of Convolutional Neural Networks For Image Classification".*

*3) Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D.,&_Rabinovich, A.(2015) "Going deeper with convolutions." in Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 1-9).*

*4) Alagappan, G.; Ong, J.R.;Yang, Z.; Ang, T.Y.L.; Zhao,W.; Jiang,Y.; Zhang,W.; Png, C.E. Leveraging AI in Photonics and Beyond. Photonics 2022, 9, 75. https://doi.org/10.3390/photonics9020075*

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*6) C. M. Chew and W. H. Weedon, "A 3d perfectly matched medium from modified Maxwell's equations with stretched coordinates", Microwave and Optical Tech. Lett., vol. 7, No. 13, pp. 599-604, 1994*

*7) https://pyimagesearch.com/2019/02/04/keras-multiple-inputs-and-mixed-data/*

*8) Gandhi Alagappan and Ching Eng Png. Prediction of electromagnetic field patterns of optical waveguide using neural network. Neural Computing and Applications, 33(7):2195– 2206, 2021.*

*9) Wei Ma, Zhaocheng Liu, Zhaxylyk A Kudyshev, Alexandra Boltasseva, Wenshan Cai, and Yongmin Liu. Deep learning for the design of photonic structures. Nature Photonics, 15(2):77–90, 2021.*