Machine learning in Imaging
Final project
Optimization of the optics lens in Classification of Colorectal Cancer Histology

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Outline

- Introduction
  - Problem identification, Data source
- Methods
  - Physical layer, CNN model, Train test split
- Results
  - Confusion matrix, Accuracy curves, Segmentation
- Conclusion

Introduction

▶ Histopathology: Microscopic examination of diseased tissue

▶ Computer-Aided Diagnosis (CAD) based on histopathological imaging

  ➢ Classification, detection and counting, segmentation, grading and prognosis prediction …
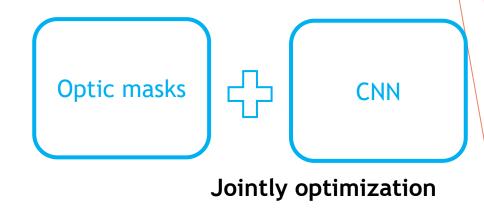
▶ Challenges:

  ➢ Medical samples: Transparent optical characteristics, contain hard-to-extracted features, when acquiring images with a normal microscope.
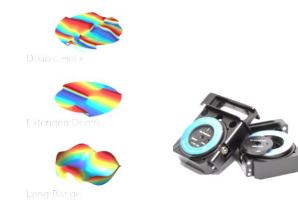
Introduction

- Objectives:
  - Design a deep learning framework and jointly optimize physical layer parameters of microscope to improve detection of cancer tissue in histology microscopy.
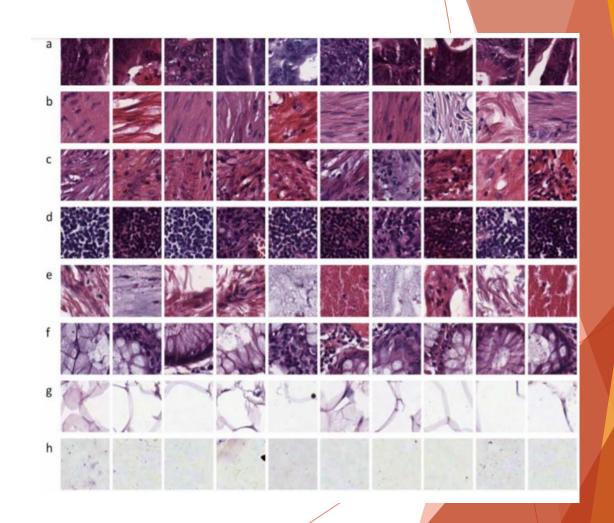
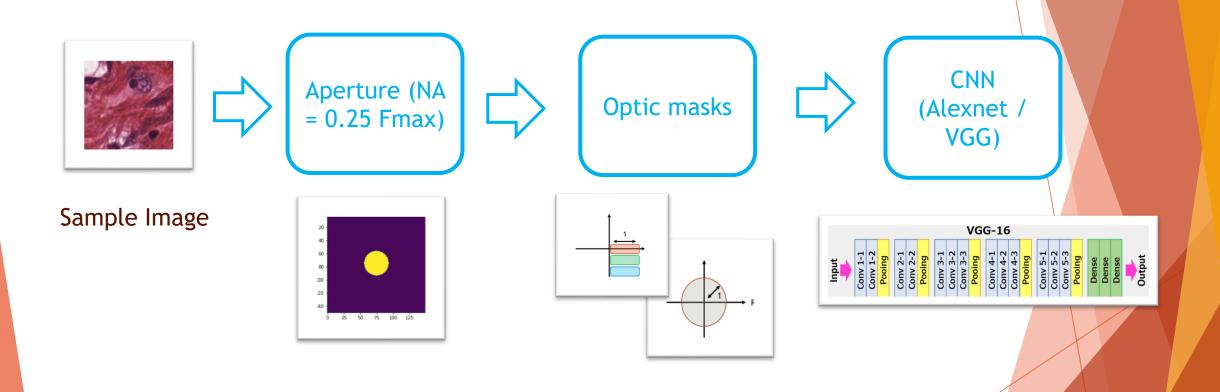 - Selected physical layer: Optics masks → feasible, practicable to fabricate and customize

Optic masks + CNN

Jointly optimization

Double Helix

Extended Depth

Long Range

Multicolor

Data Source: Colorectal Cancer Histology

- 150 x 150 x 3 RGB colorectal histology (total 5000 images)
- 8 categories
  - (a) tumor epithelium
  - (b) simple stroma
  - (c) complex stroma (stroma that contains single tumor cells and/or single immune cells)
  - (d) immune cell conglomerates
  - (e) debris and mucus
  - (f) mucosal glands
  - (g) adipose tissue
  - (h) background
- 10 larger images (5000x 5000)
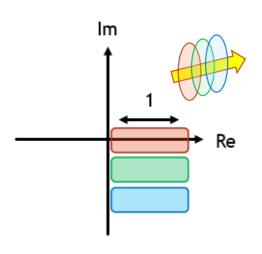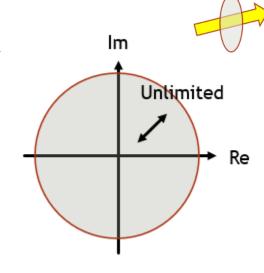
Overall Architecture

Sample Image

Aperture (NA = 0.25 Fmax)

Optic masks

CNN (Alexnet / VGG)

Physical Layers: Optic Mask

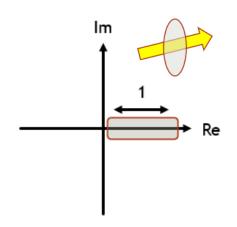- A RGB color filter (absorption) mask
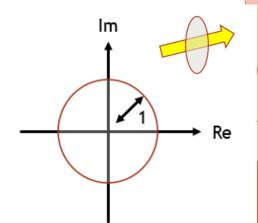
- A phase mask without weight constraint

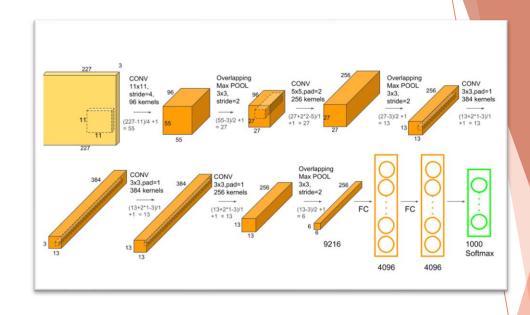- An absorption mask constraint weight magnitude range from
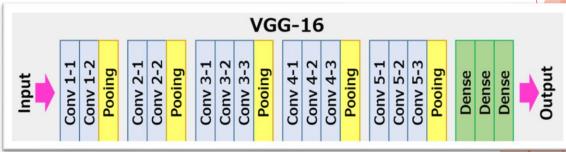
  0 - 1

- A phase mask with constraint weight magnitude = 1

CNN

▶ Alexnet

➢ 5 convolutional layers

+ 3 fully connected layers

▶ VGG16

➢ 16 layers with consistent shape

- **Drop out 40% in dense layer**
- **10 epoch**
- **32 batch size**

Train Test Split

5000 Small mages (5000,150,150,3)

10 Large image
(10,5000,5000,3)

**Sliding windows
(size = 150 x 150)**

...

Training Data: 75%

Validation
data : 25%
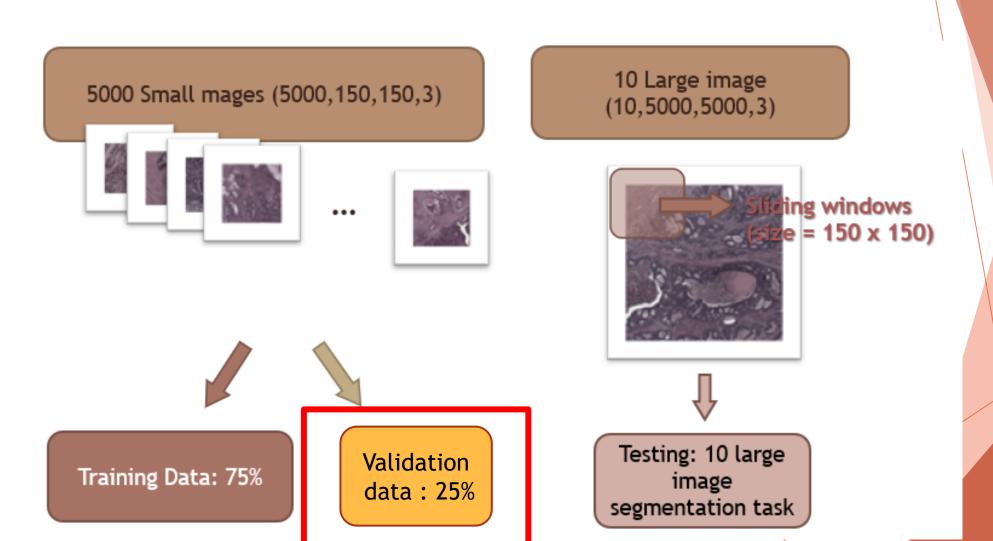
Testing data: 10
large image
segmentation task

Results : Validation Results

Results: Performance Comparison
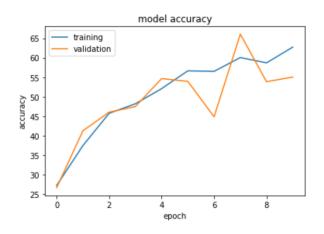
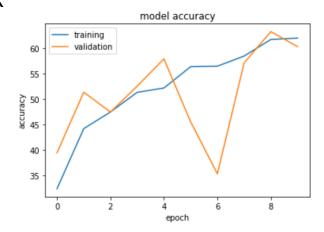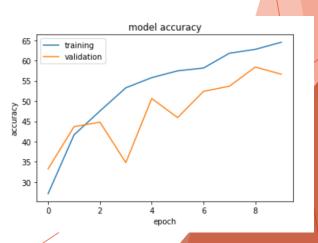| Physical \ CNN	Training		Validation	
	Alexnet	VGG16	Alexnet	VGG16
RGB filter	**62.74%**	14.72%	**66.08%**	13.52%
Real value absorption mask	61.73%	14.76%	63.27%	13.44%
Unconstraint phase mask	**69.78%**	16.21%	**69.12%**	12.14%
Constraint phase mask	64.53%	12.88%	56.64%	11.08%

Results: Accuracy v.s Epoch

RGB filter

Unconstraint phase mask
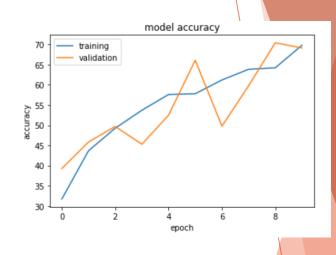
Real value absorption mask
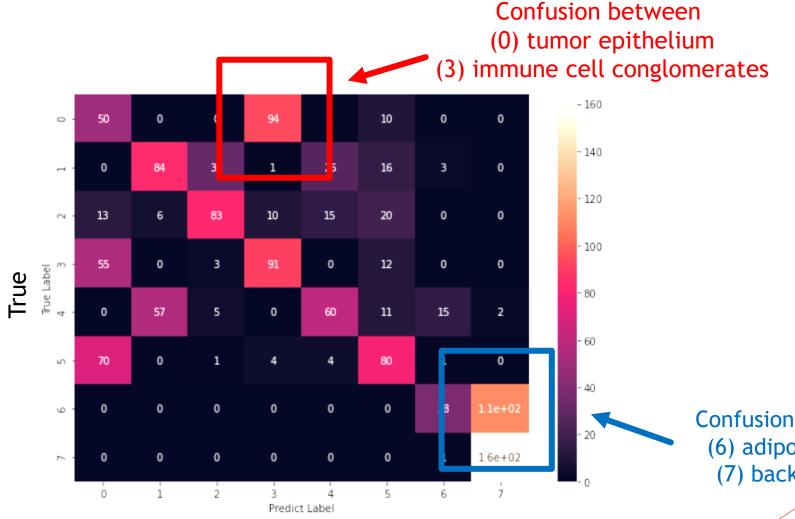

Constraint phase mask

Results: Confusion Matrix
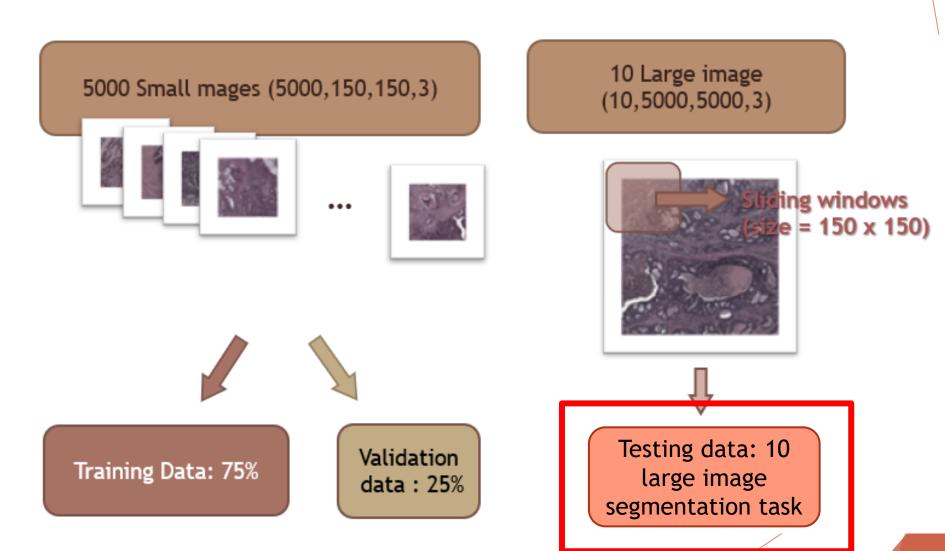
(0) tumor epithelium
(1) simple stroma
(2) complex stroma
(3) immune cell conglomerates
(4) debris and mucus
(5) mucosal glands
(6) adipose tissue
(7) background.

Confusion between
(0) tumor epithelium
(3) immune cell conglomerates

Confusion between
(6) adipose tissue
(7) background

Final Testing (Segmentation) Results

5000 Small mages (5000,150,150,3)

10 Large image
(10,5000,5000,3)

Sliding windows
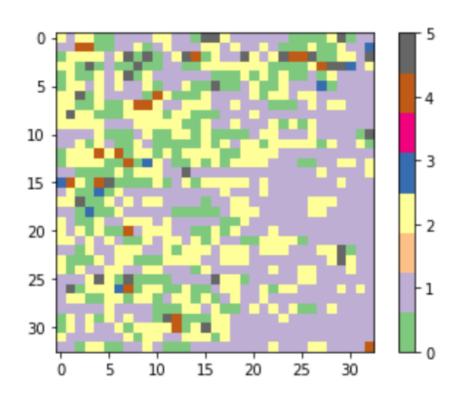(size = 150 x 150)

Training Data: 75%

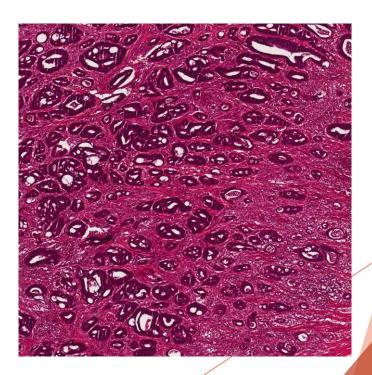Validation
data : 25%

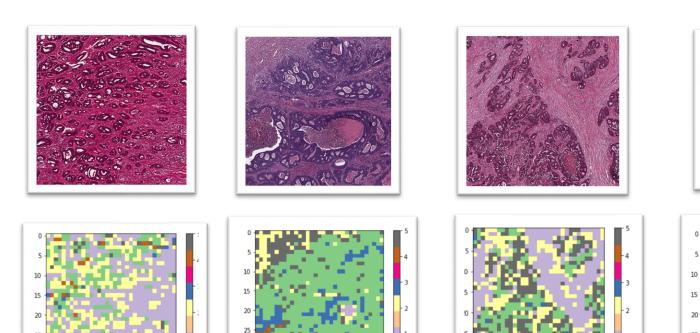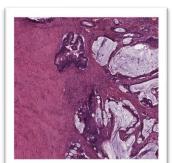Testing data: 10
large image
segmentation task

Results:
Large Image Segmentation

7 background
6 adipose tissue
5 mucosal glands
4 debris and mucus
3 immune cell conglomerates
2 complex stroma
1 simple stroma
0 tumor epithelium
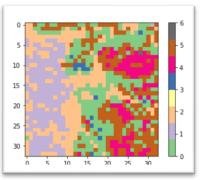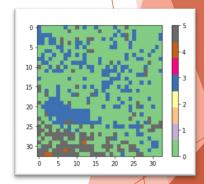
Completed segmentation results: 1 - 5
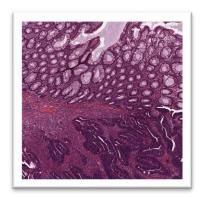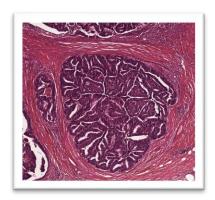

3 immune cell conglomerates
2 complex stroma
1 simple stroma
0 tumor epithelium
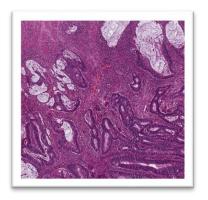
7 background
6 adipose tissue
5 mucosal glands
4 debris and mucus
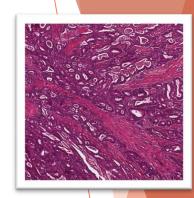
Completed segmentation results: 6 - 10

3 immune cell conglomerates

7 background

2 complex stroma

6 adipose tissue

1 simple stroma

5 mucosal glands

0 tumor epithelium

4 debris and mucus

Conclusion and Future Work

▶ Unconstraint phase mask: Best result, but hard to implement

▶ RGB filter: cost-effective

▶ Future works:

  ➢ Prevent false negative instance

  ➢ Fine-tune CNN hyper-parameters, Transfer learning

Thank you for listening

Reference

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Appendix

Appendix

A intestinal lumen   5 mm

B   5 mm   intestinal lumen

ADI
BACK
DEB
LYM
MUC
MUS
NORM
STR
TUM