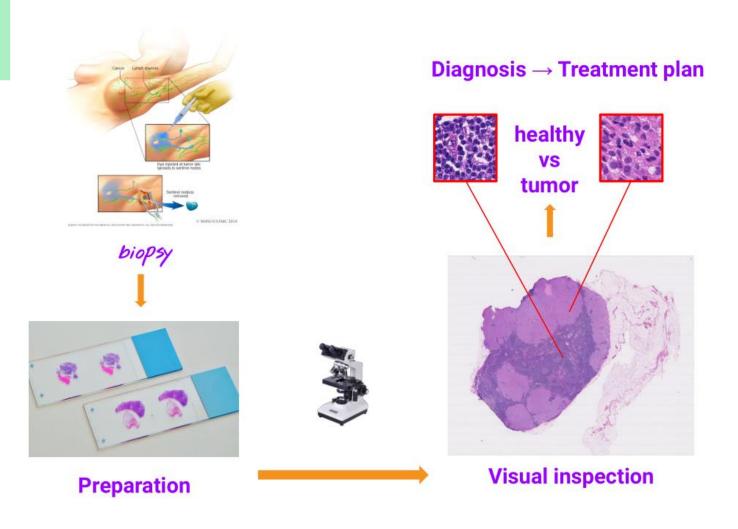
ADL Project Presentation

Detecting cancerous cells in gigapixel images

zc2492

Context (Goal)

For cancer diagnosing!



Problem: Pathologists make mistakes when diagnosing biopsied tissue

Solve: Develop a tool to assist physicians and reduce misdiagnosis rate

Context (Dataset)

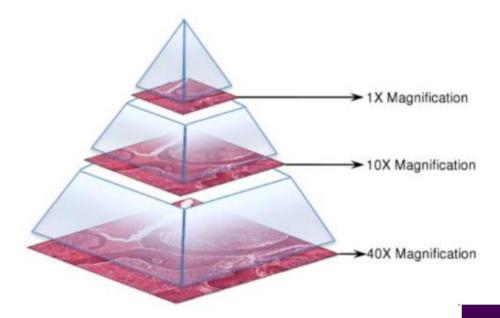
Dataset is from **CAMELYON16**: https://camelyon16.grand-challenge.org/Data/ (given by Professor Joshua)

Different Pathology Images

Different resolution levels(0-7)

Has both cells images and tumor mask

Tumor mask: channel 0, value of tumor pixel is 1, other is 0



Methodology

single or multi

Input(s)

patches

CNN

Single scale

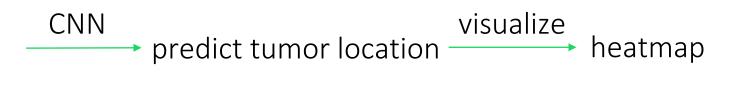
fully connected

Multi scale

fully connected

- different Pathology

 Images with one/different resolution levels
- unseen Pathology Images
 patches (consistent with training)



end-to-end prototype of detecting cancer !!!

extract

Single Input

different Pathology Images with specific level (level 4)

extract Input CNN

unseen Pathology Images

patches (consistent with training)

CNN predict tumor location visualize heatmap

single

Single scale

fully connected



end-to-end prototype of detecting cancer !!!

Extract patches---predefined functions

Patch size: 299 x 299

Center size: 128 X 128

def read_slide: convert a region of slide to RGB array

def find_tissue_pixels: get coordinates of tissue in this region

def apply_mask: return a image where the color of tissue pixel is (1,0,0), other are grey

def get_patches:

Get image patches, image mask patches and tissue patches based on the center (x0, y0) at the specific resolution level

def check center:

Check whether the center of a patch has tumor

Extract patches---collect patches

Patch size: 299 x 299

Center size: 128 X 128

def get_dataset:

>>> Input: level, patch_size, patch_center, select_image (list)

>>> output: dataset_patch, dataset_label

Detail, for each image:

- 1. Get tumor and health pixels coordinates from the single resolution level
- 2. Pick 500 samples in both tumor and health pixels as (x0, y0)
- 3. If the tissue in the related patch is more than 50% of this patch, collect this patch, 100
- 4. Record the related label (tumor or health) of this patch

Extract patches---collect patches

Patch size: 299 x 299

Center size: 128 X 128

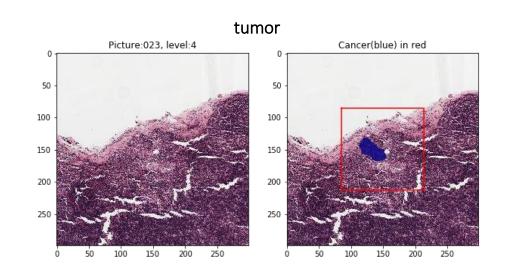
Training images: (10)

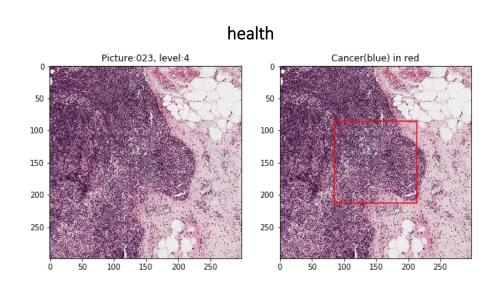
'016','023','035','057','059','064','075','081','094','096'

Test image: (1)

'110'

So I totally have 200*10 = 2000 training samples 200 test samples





Preprocessing

Patch size: 299 x 299

Center size: 128 X 128

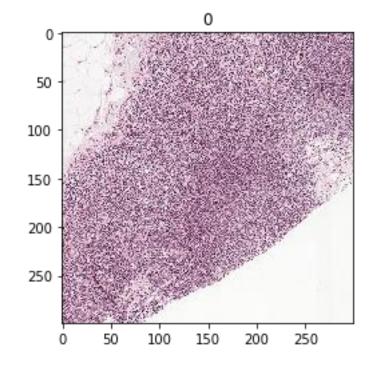
Split training data training : validation = 8 : 2



patch_train shape:(1600, 299, 299, 3)
patch_val shape:(400, 299, 299, 3)
patch_test shape:(200, 299, 299, 3)

rescale image to [0,1]

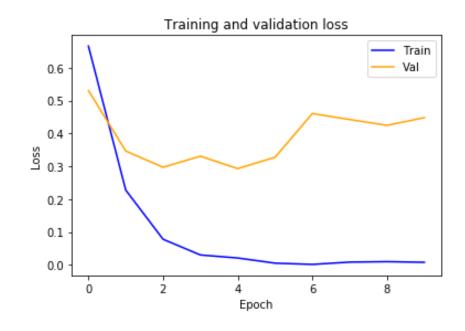
set batch = 32

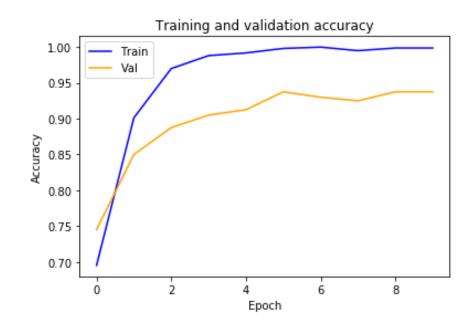


Patch size: 299 x 299

Center size: 128 X 128

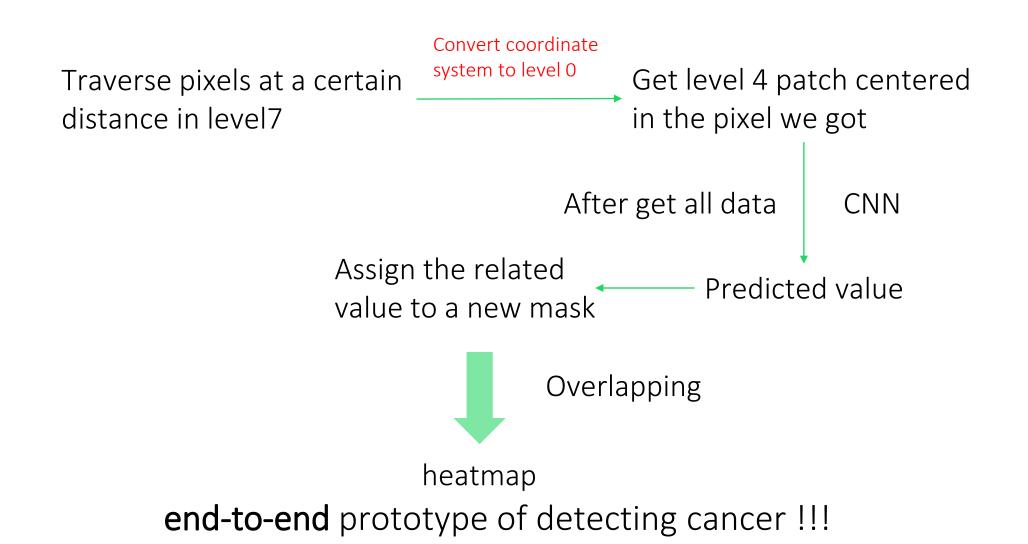
Use CNN model defined by myself:



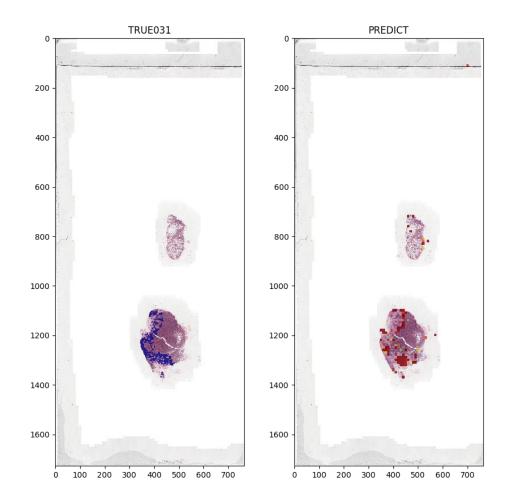


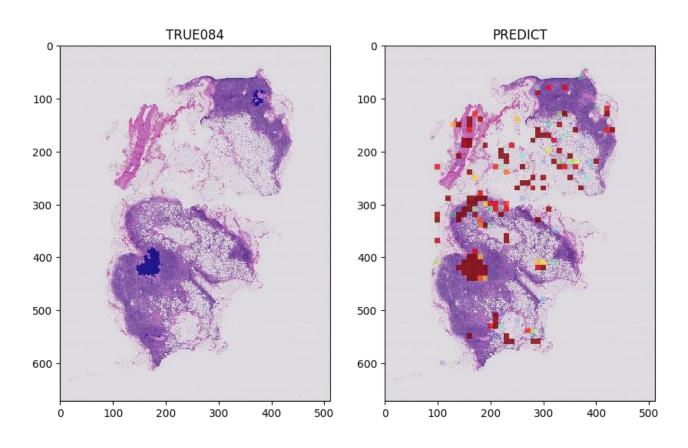
Evaluate the model: Test loss: 0.280, accuracy: 0.835

To Colab



Heapmap with single input (unseen data)





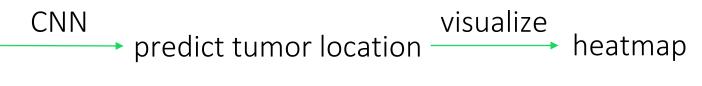
Multi Input



Multi scale

fully connected

unseen Pathology Images
patches (consistent with training)



Multi



end-to-end prototype of detecting cancer !!!

Extract patches---collect patches

Patch size: 299 x 299

Center size: 128 X 128

def get_dataset:

>>> Input: level, patch_size, patch_center, select_image (list)

>>> output: dataset_patch, dataset_label

Detail, for each image:

- 1. Get tumor and health pixels coordinates from the single resolution level
- 2. Pick 500 samples in both tumor and health pixels as (x0, y0)
- 3. If the tissue in the related patch is more than 50% of this patch, collect this patch
- 3.5 add the patch in level 5 and 6 with same size, centered in same (x0, y0)
- 4. Record the related label (tumor or health) of this patch

Extract patches---collect patches

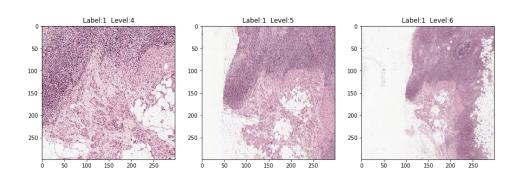
Patch size: 299 x 299

Center size: 128 X 128

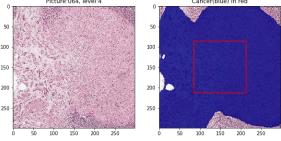
So I totally have 200*10*3 = 6000 training samples test samples

After split:

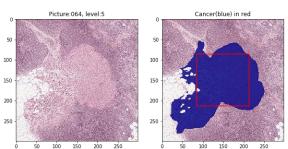
patch_train_4 shape: (1600, 299, 299, 3) patch_val_4 shape: (400, 299, 299, 3) patch_test_4 shape: (200, 299, 299, 3) patch_train_5 shape: (1600, 299, 299, 3) patch_val_5 shape: (400, 299, 299, 3) patch_test_5 shape: (200, 299, 299, 3) patch_train_6 shape: (1600, 299, 299, 3) patch_val_6 shape: (400, 299, 299, 3) patch_test_6 shape: (200, 299, 299, 3)



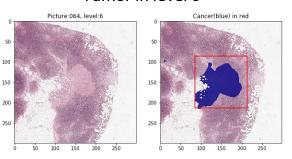
Tumor in level 4 Picture:064 level:4 Cancer(blue) in red



Tumor in level 5



Tumor in level 6



Model

To Colab

Patch size: 299 x 299

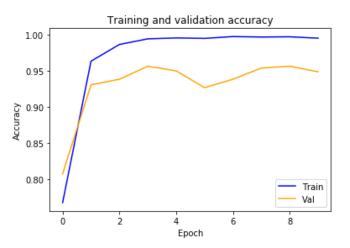
Center size: 128 X 128

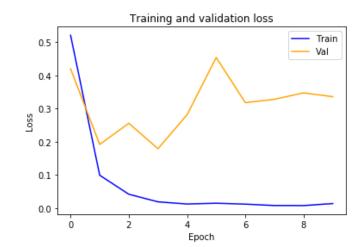
Use CNN model defined by myself: have three inputs

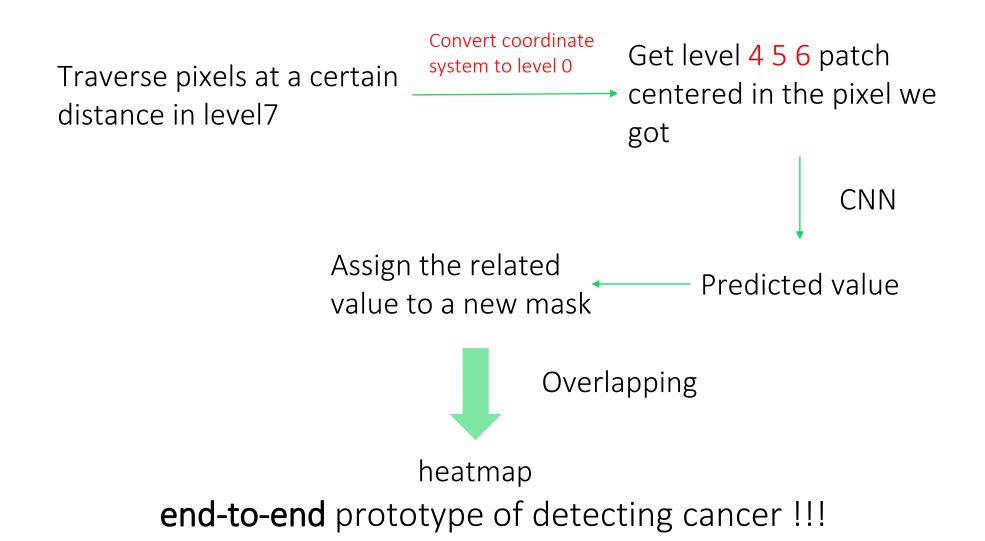
| Layer (type) | Output Shape | Param # | Connected to |
|---------------------------|--------------------|----------|--|
| input_1 (InputLayer) | [(None, 299, 299, | 3) 0 | |
| input_2 (InputLayer) | [(None, 299, 299, | 3) 0 | |
| input_3 (InputLayer) | [(None, 299, 299, | 3) 0 | |
| sequential (Sequential) | (None, 74, 74, 32) | 11936 | input_1[0][0] |
| sequential_1 (Sequential) | (None, 74, 74, 32) | 11936 | input_2[0][0] |
| sequential_2 (Sequential) | (None, 74, 74, 32) | 11936 | input_3[0][0] |
| concatenate (Concatenate) | (None, 74, 74, 96) | 0 | sequential[0][0] sequential_1[0][0] sequential_2[0][0] |
| flatten (Flatten) | (None, 525696) | 0 | concatenate[0][0] |
| dense (Dense) | (None, 128) | 67289216 | flatten[0][0] |
| dropout (Dropout) | (None, 128) | 0 | dense[0][0] |
| dense_1 (Dense) | (None, 1) | 129 | dropout[0][0] |

Total params: 67,325,153 Trainable params: 67,324,769 Non-trainable params: 384

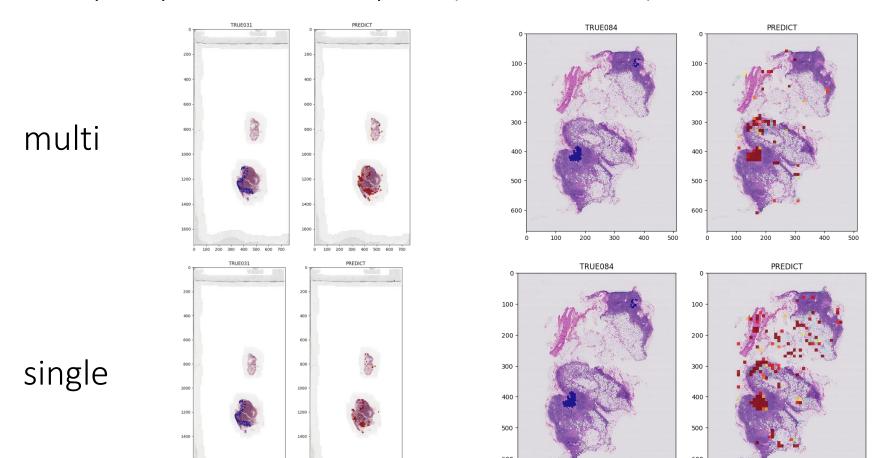
Evaluate the model: Test loss: 1.938, accuracy: 0.809





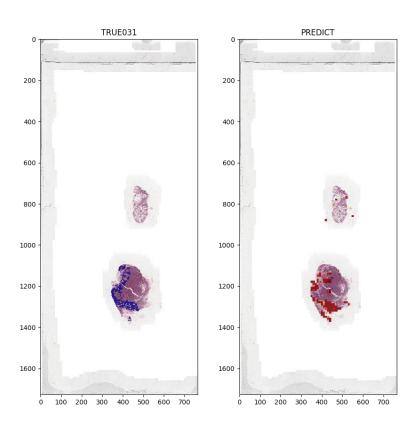


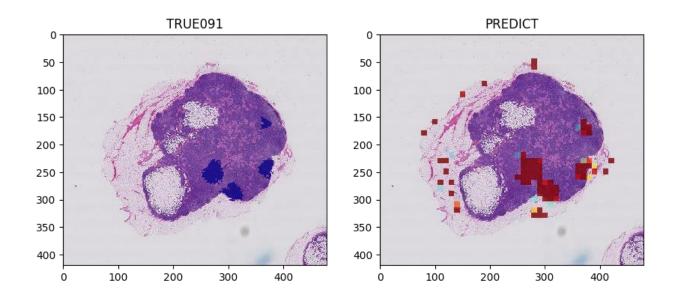
Heapmap with multi inputs (unseen data)



Multi perform better than single

More heapmap with multi inputs (unseen data)





Improve

Increase the number of training set

Use data augmentation to generate more data since tumor number is small

Thank you