

# Applied Deep Learning Project

Detecting Cancer Metastases on Gigapixel Pathology Images



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Major : MSBA

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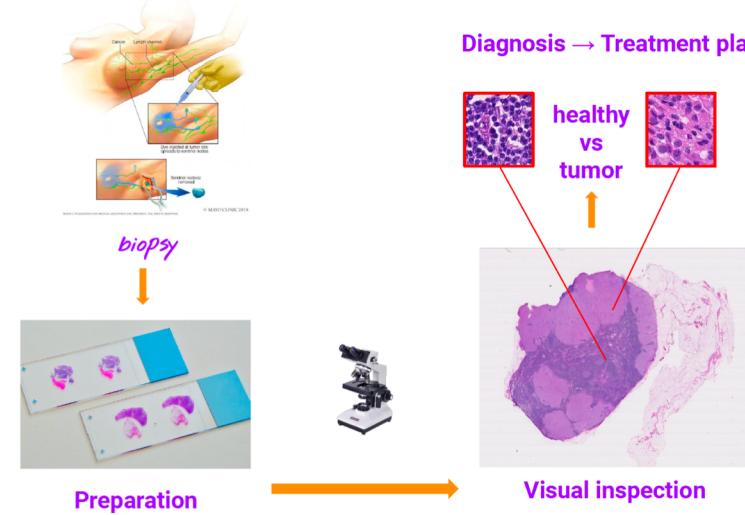
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# 01- Motivation

# 01-Motivation



Source: Applied deep learning slides

- ◆ Microscopic examination of lymph nodes **is crucial** in breast cancer staging<sup>[1]</sup>
- ◆ Currently the manual process **requires highly skilled pathologists** <sup>[1]</sup>
- ◆ Fairly **time-consuming and error-prone**, particularly for lymph nodes with either no or small tumors <sup>[1]</sup>

[1] Liu, Yun, et al. "Detecting cancer metastases on gigapixel pathology images." *arXiv preprint arXiv:1703.02442* (2017).

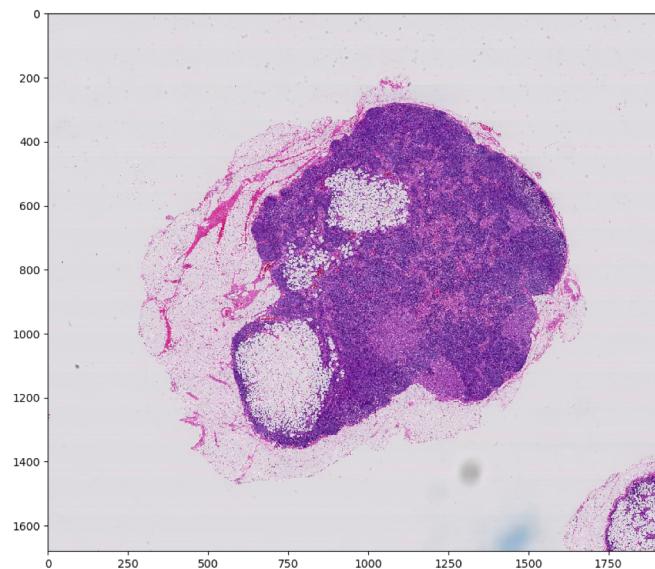


## 02- Methods

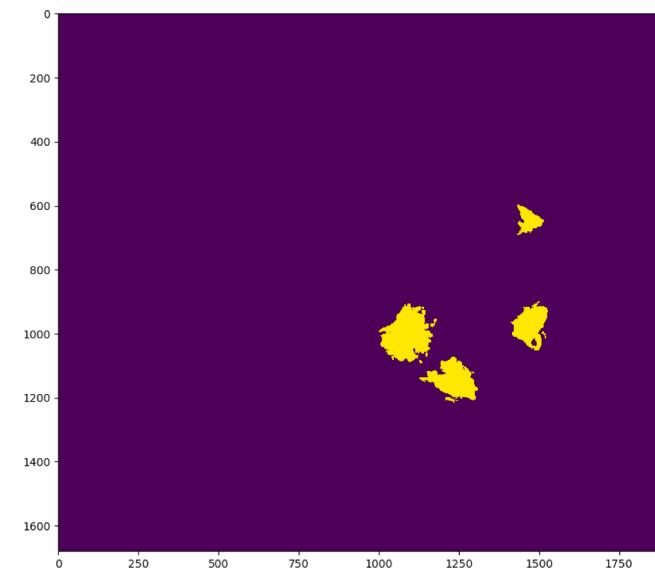
## 02-Methods

### Data Preprocessing

- ◆ Raw Data: 22 Gigapixel Pathology Images, each has a tumor slide and a corresponding mask
- ◆ Sanity check: Remove slide 38 because it doesn't have correspond mask



Tumor Slide (Actual Images)

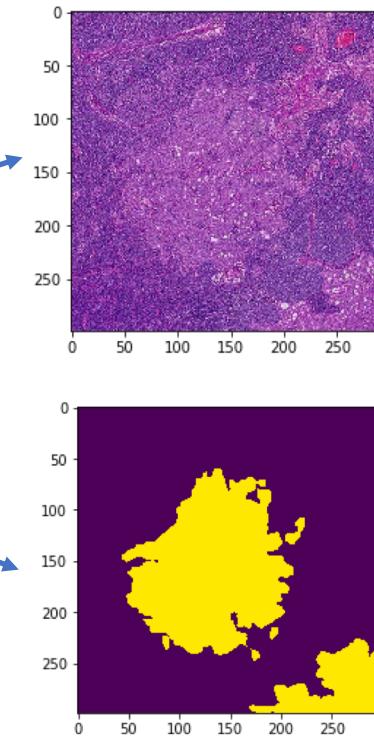
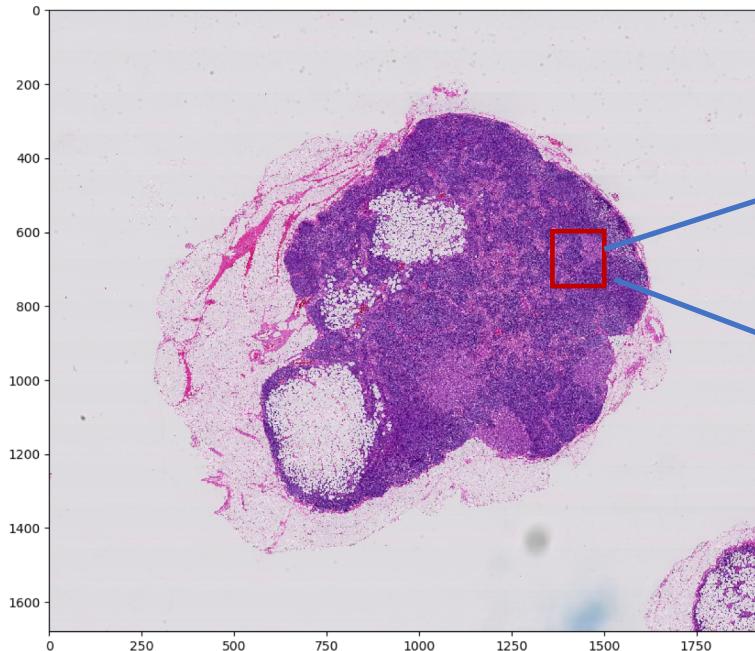


Tumor Mask (Tumor Location)

## 02-Methods

### Data Preprocessing

- ◆ Train-Validation-Test Split: 16 Images for train, 2 Images for validation, 3 Images for test
- ◆ Create train/validation set: Sample images with size (299, 299) from raw Gigapixel Pathology Images at different zoom level (level 0 and 1)

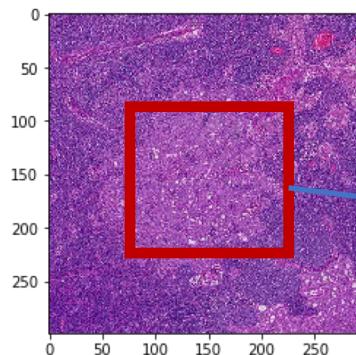


## 02-Methods

### Data Preprocessing

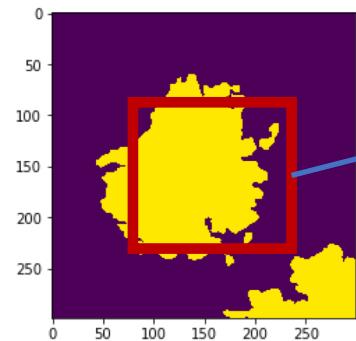
- ◆ Balanced dataset: Select "normal" or "tumor" with equal probability.
- ◆ Enhanced dataset: Only contains images contains at least 30% tissue.
- ◆ Simplified target: If tumor exist in the center 199x199 area, then label it tumor else normal

**Tumor Slide**



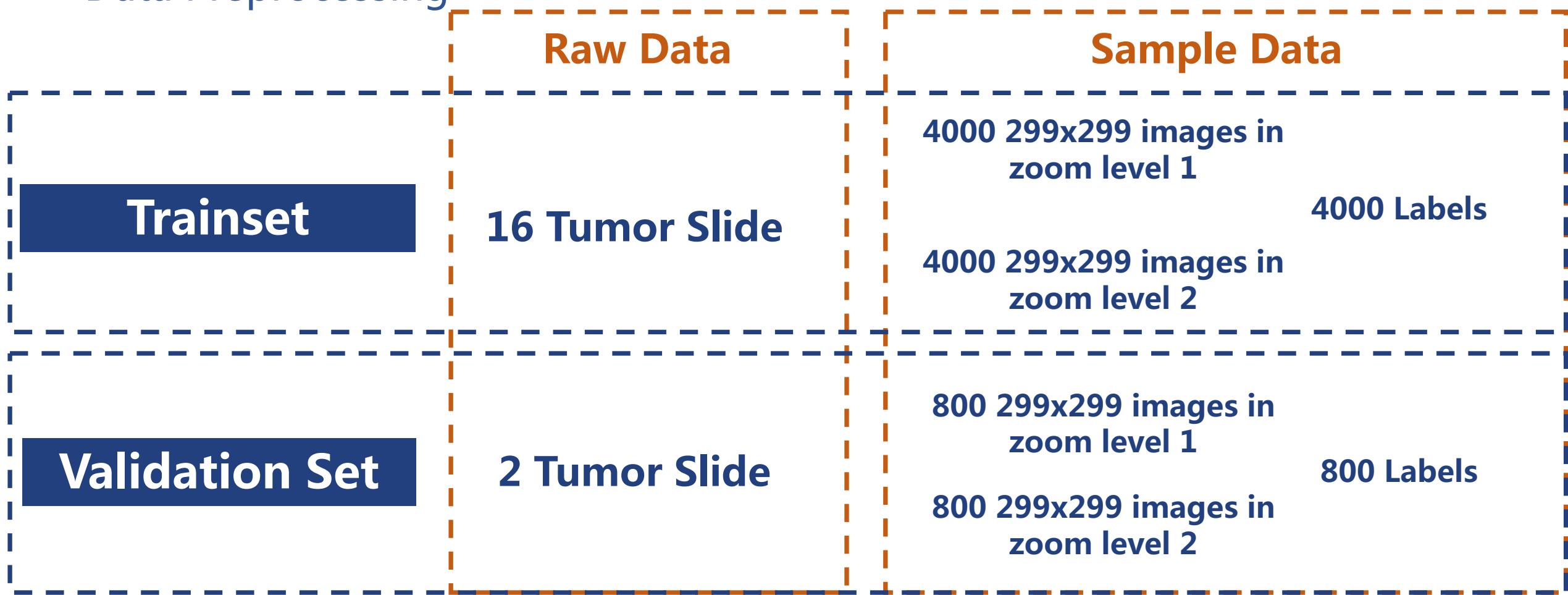
**If tumor exist, then label it tumor  
Else, label it normal**

**Tumor Mask**



## 02-Methods

### Data Preprocessing



## 02-Methods

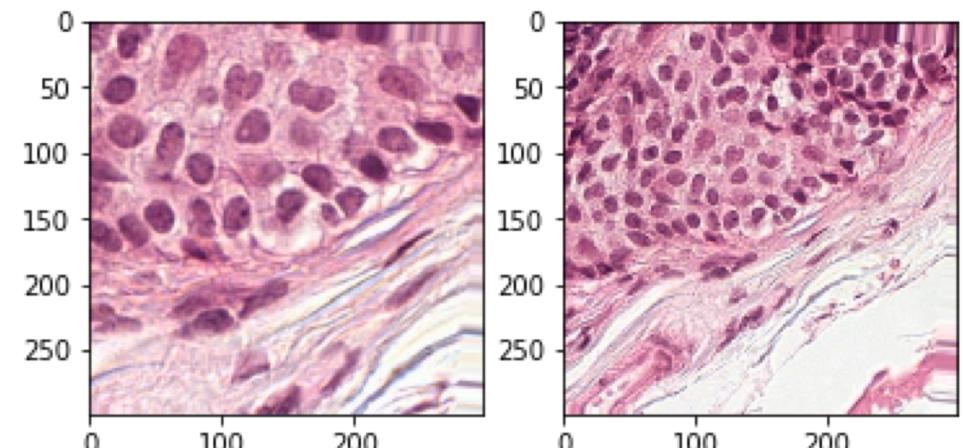
### Data Augmentation

- ◆ Use Keras ImageDataGenerator to augment data

- ◆ Horizontal\_flip
- ◆ Vertical\_flip
- ◆ Rescale
- ◆ Width\_shift
- ◆ Height\_shift
- ◆ Rotation

- ◆ Use TensorFlow image random to augment data

- ◆ Random brightness
- ◆ Random saturation
- ◆ Random hue
- ◆ Random contrast

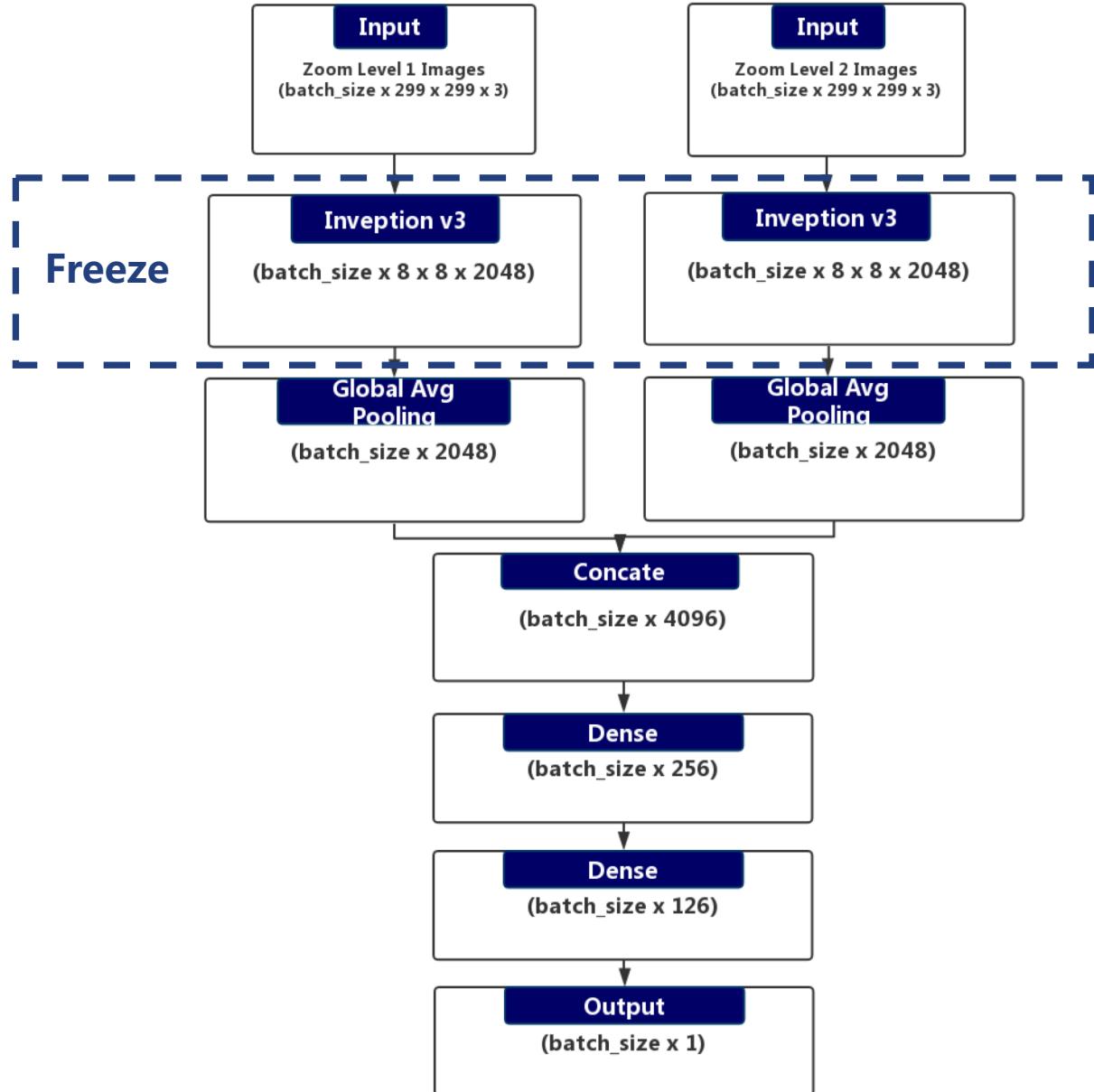


Sample augmentation result

# 02-Methods

## Modeling

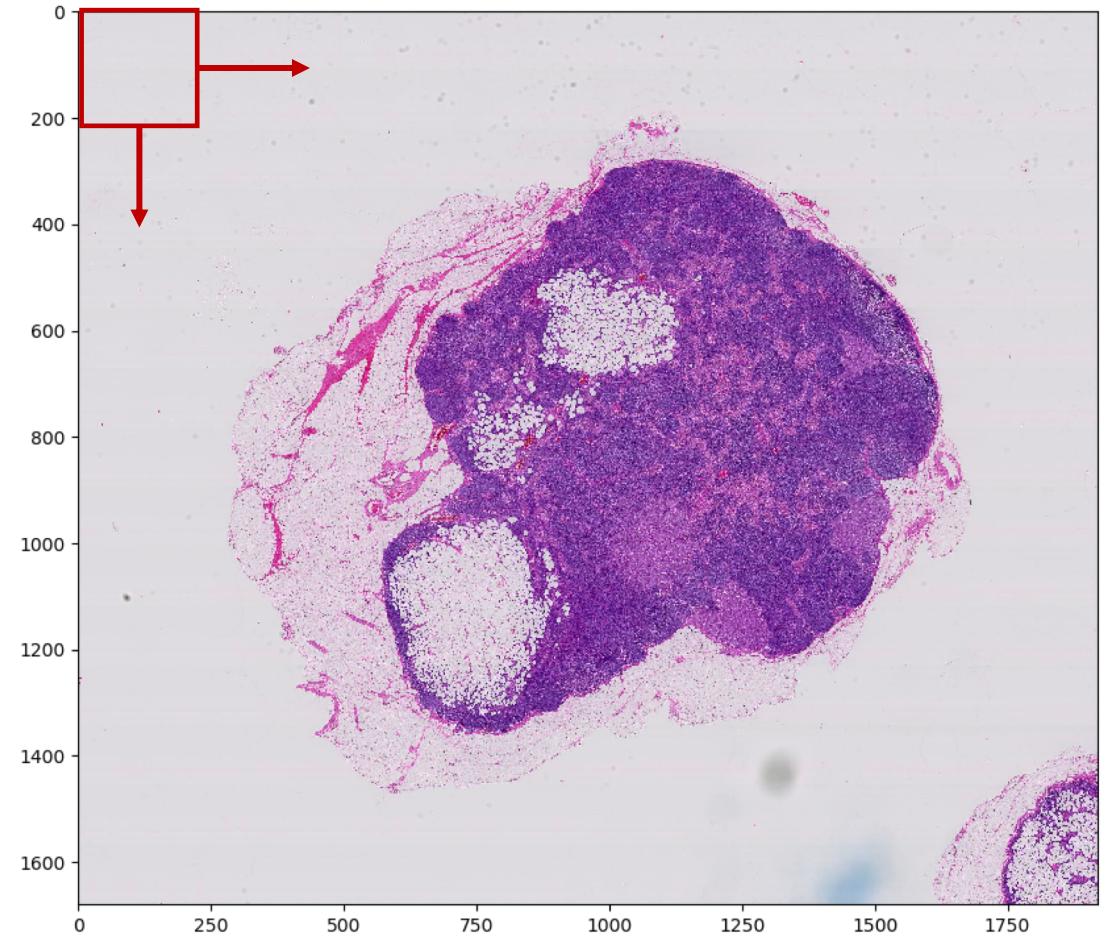
- ◆ Use Pretrained inception v3 model on Images
- ◆ Use Global Avg Pooling layer to reduce parameter
- ◆ Concatenate activations from processing two zoomed images to make joint prediction



# 02-Methods

## Prediction

- ◆ Generate 299 x 299 patches from the test set images rows by rows, columns by columns
- ◆ Make prediction on each patches
- ◆ Set a threshold and make predictions



## 03- Results

# 03-Results

## Evaluation Matrices

### Precision

$$Precision = \frac{true\ positive}{true\ positive + false\ positive}$$

### Recall

$$Recall = \frac{true\ positive}{true\ positive + false\ negative}$$

### F1 - Score

$$F1\ Score = 2 * \frac{precision * recall}{precision + recall}$$

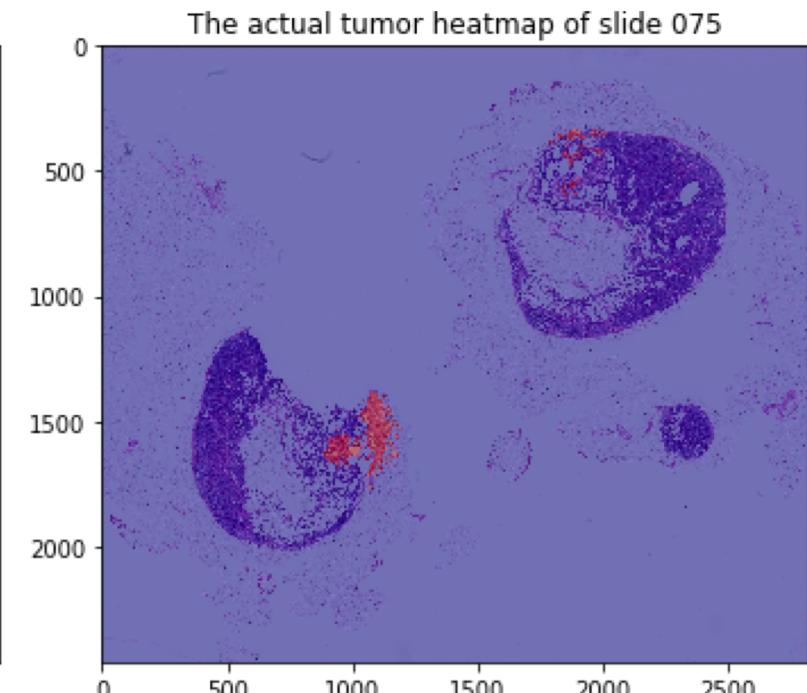
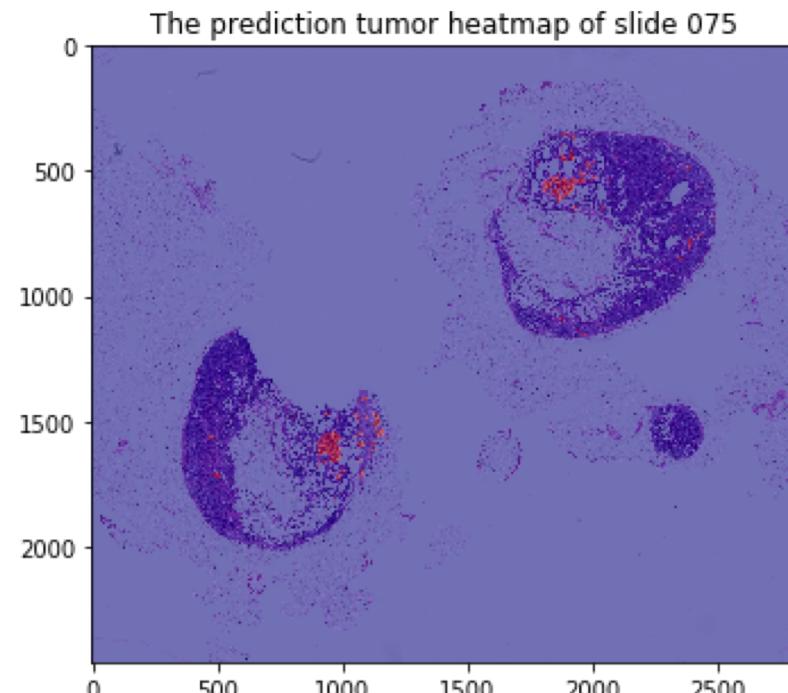
### AUC

		Prediction	
		Tumor	Normal
Actual	Tumor	True Positive	False Negative
	Normal	False Positive	True Negative

# 03-Results

## Test set evaluation

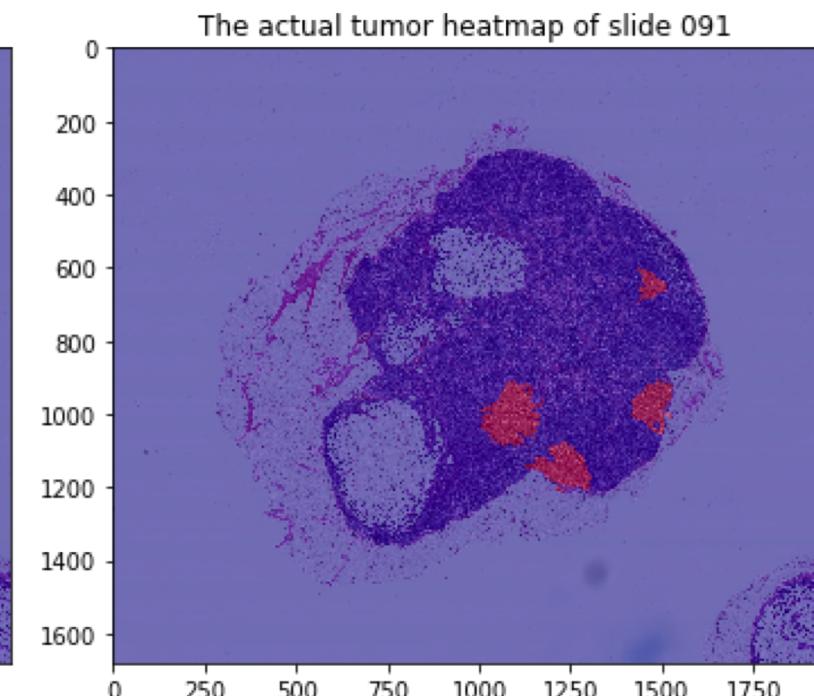
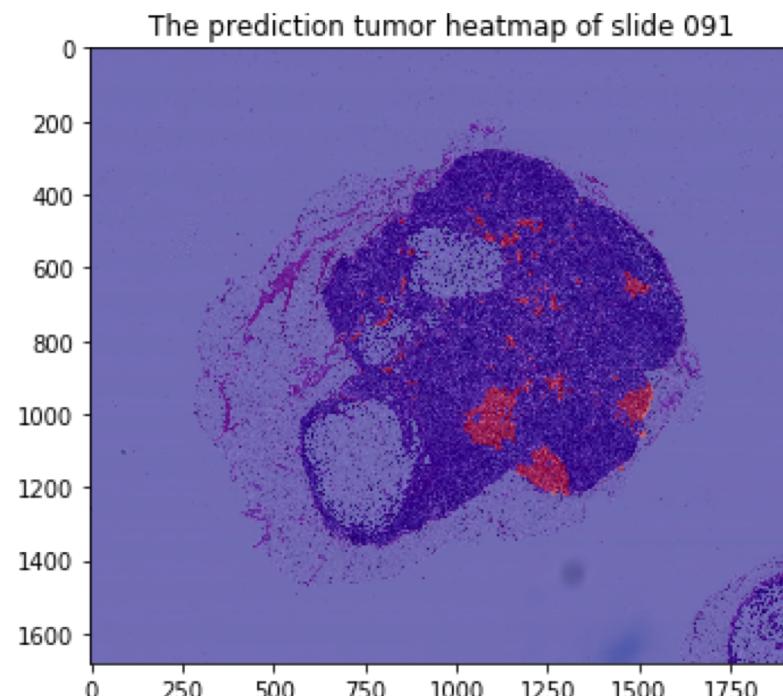
Matrix	Result
AUC	0.9713
Precision	0.4678
Recall	0.3855
F1 Score	0.4227



# 03-Results

## Test set evaluation

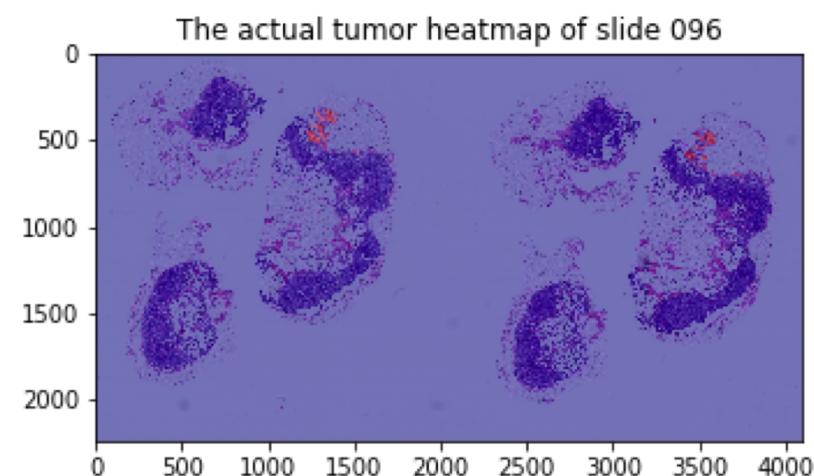
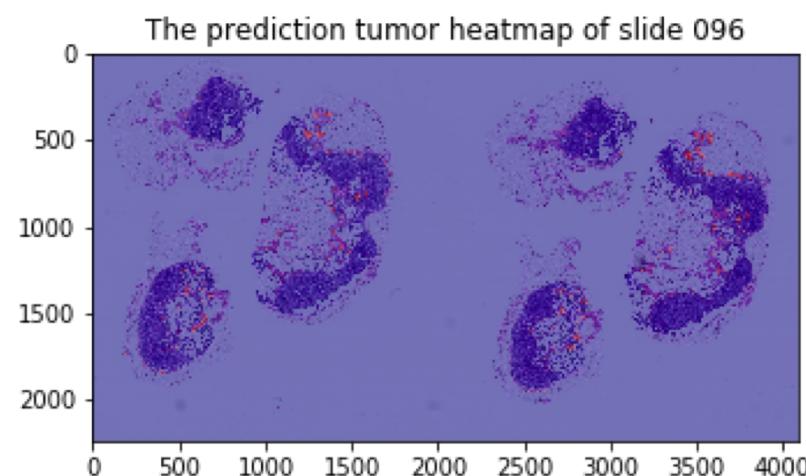
Matrix	Result
AUC	0.9884
Precision	0.5126
Recall	0.7288
F1 Score	0.6019



# 03-Results

## Test set evaluation

Matrix	Result
AUC	0.9719
Precision	0.1826
Recall	0.4572
F1 Score	0.2609





## 04- Conclusions

## 04-Conclusion

Our prototype works quite, but still have a lot to improve

- ◆ Train a new model without using pretrained parameters
- ◆ Include more dataset and sample more patches
- ◆ Buy more GPUs and RAM! And increase batch size

THANKS