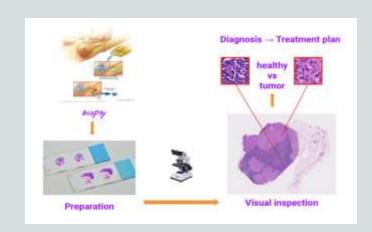
Detecting Cancer Metastasis on Gigapixel Pathology Images

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Motivation

- Microscopic examination of lymph nodes for breast cancer staging is crucial but can be tedious & error-prone.
- When tissue samples are sliced, they can have many images/samples which can make the process time-consuming.
- Requires highly skilled pathologist.



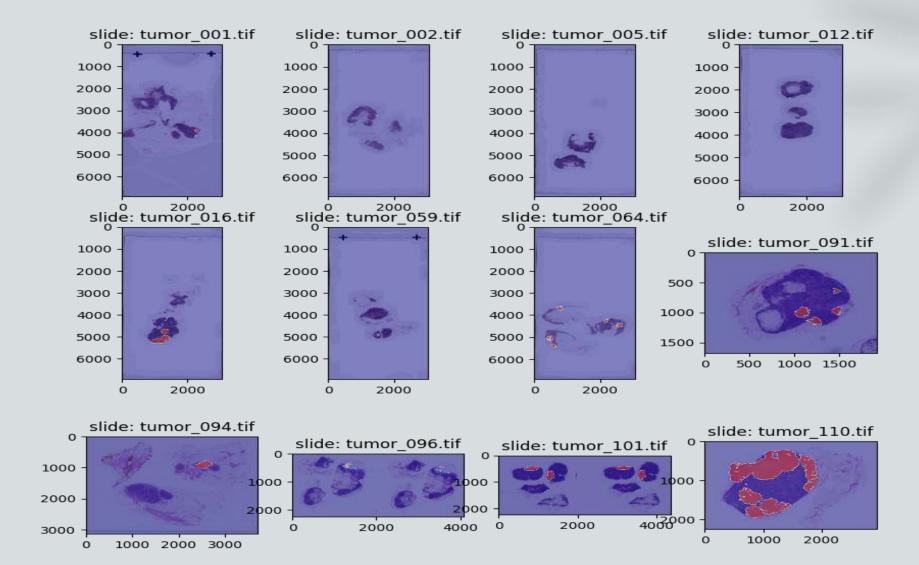
Goal

 To detect and classify breast cancer metastasis and reconstruct the tumor probability heat map using Camelyon16 dataset.

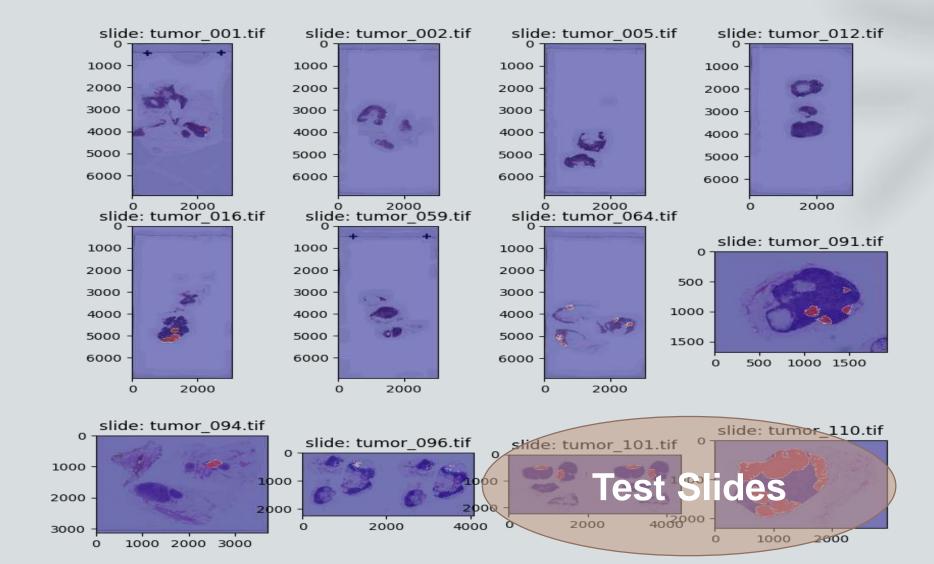
Camelyon16 (Dataset)

- 22 Gigapixel pathology images, each with a slide & tumor masks.
- Each slide has different zoom levels of magnification.
- Used 12 slides & 3 zoom level for this project.

Zoom Level 5 – 12 Slides & Masks



Zoom Level 5 – 12 Slides & Masks



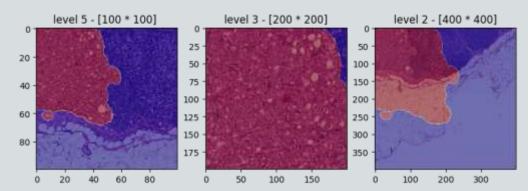
Data Processing - Algorithm

- For each slide at a specific zoom level ("5") in training data
 - Extract a particular patch (100 * 100) of a specific size, from slide
 - Check if that patch has at least 20% tissue pixels (pixel intensity <= 0.8)
 - Extract a patch of 200 * 200 (patch size (100) * zoom factor (2)) from zoom level 3 and crop a 100 * 100 image from center.
 - Extract a patch of 400 * 400 (patch size (100) * zoom factor (4)) from zoom level 2 and crop a 100 * 100 image from the center
 - Assign label cancerous if mask image at the center has at least one pixel to be "1

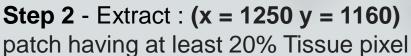
Data Processing on slide 091 at Level 5

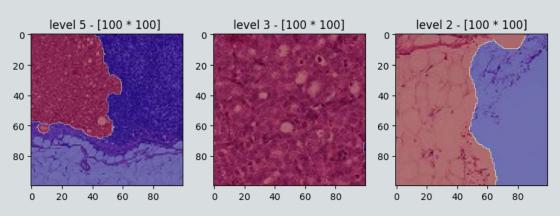


Step 1: Slide & Masks - Level 5



Step 3 – For the same pixel, Extract 200 * 200 & 400 * 400 from zoom level 3 & 2 respectively





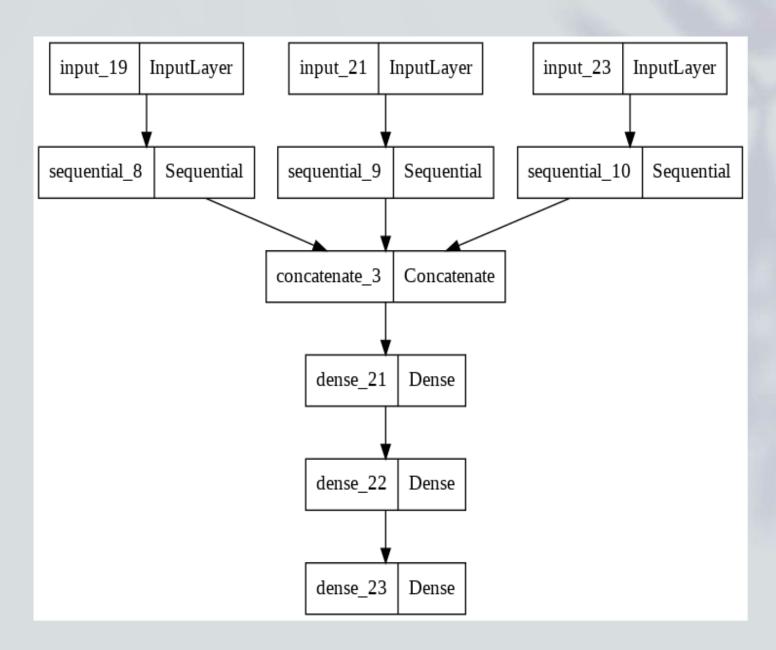
Step 4 – Crop all 3 images into 100 * 100 pixels from center

Experiments

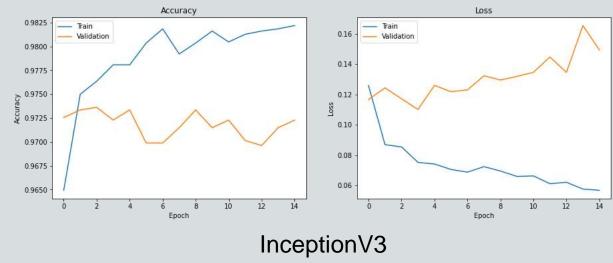
Zoom Level	Patch Size	Threshold for Tissue Pixels	Non Cancerous Patches	Cancerous Points
[5, 3, 2]	100 * 100	10	1781	87
[5, 3, 2]	100 * 100	20	2347	97
[4, 3, 2]	75 * 75	10	4289	140
[4, 3, 2]	75 * 75	20	12503	446

Modelling

- All models use Adam optimizer and Binary Cross Entropy Loss Function.
- We use Validation split of 0.3 and train for 15 epochs.
- We have trained the following 3 different models and we compare their results using the same hyperparameters.
 - InceptionV3
 - VGG16
 - MobileNet

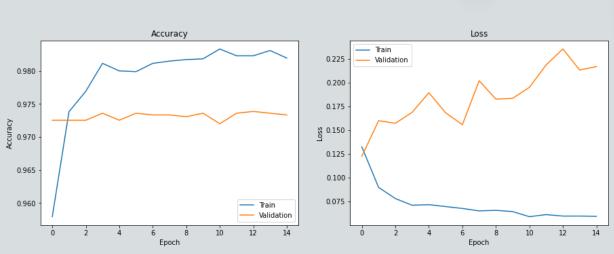


Training Metrics



Loss Accuracy - Train - Train Validation Validation 0.13 0.975 0.12 0.11 0.970 · 0.10 -0.09 0.965 0.08 0.960 Epoch Epoch

VGG16



MobileNet

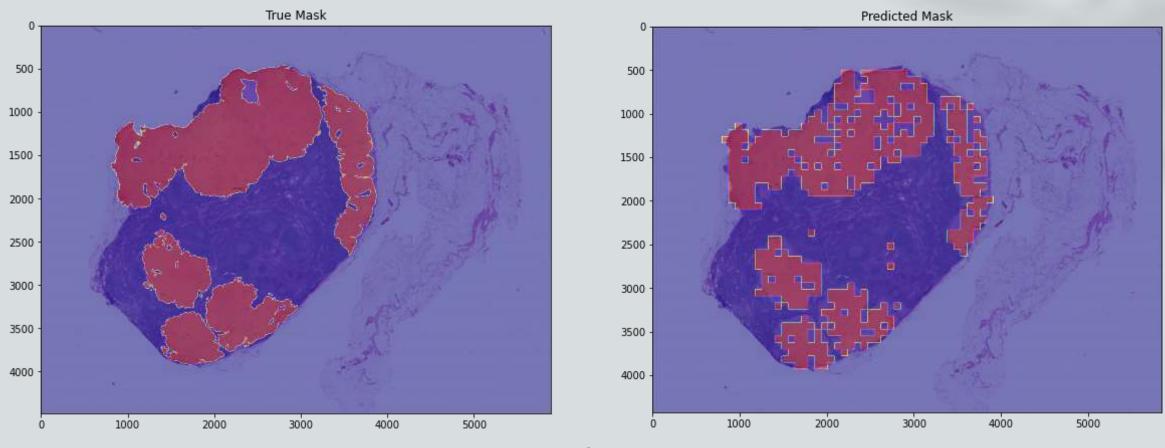
Results

	Precision		Recall		F1-Score	
	Slide 101.tif	Slide 110.tif	Slide 101.tif	Slide 110.tif	Slide 101.tif	Slide 110.tif
Inception	0.90	1.00	0.35	0.42	0.51	0.59
VGG-16	0.95	0.99	0.57	0.67	0.71	0.80
MobileNet	0.91	1.00	0.42	0.43	0.57	0.59

Conclusion

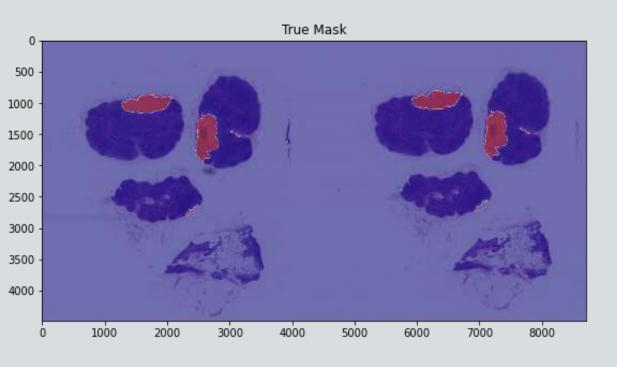
- For diagnosis of cancer using medical images, it is of utmost importance to make sure that all positive cases are detected, even if it at the expense of a few False Positives.
- Recall is a measure of how many actual positive cases were detected.
 Hence our objective is to maximize recall.
- VGG-16 shows the highest recall values for both test slides. Hence, we can safely conclude that it is the best performing model for cancer diagnosis in this context.

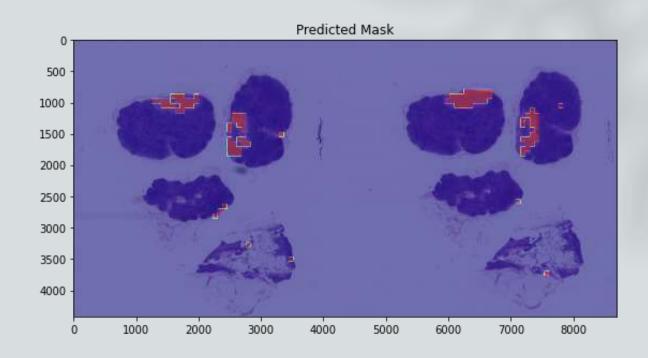
VGG16 - Mask Prediction



Test Slide 110

VGG16 - Mask Prediction





Test Slide 101