

Camelyon 16 - Medical Imaging

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Problem Statement

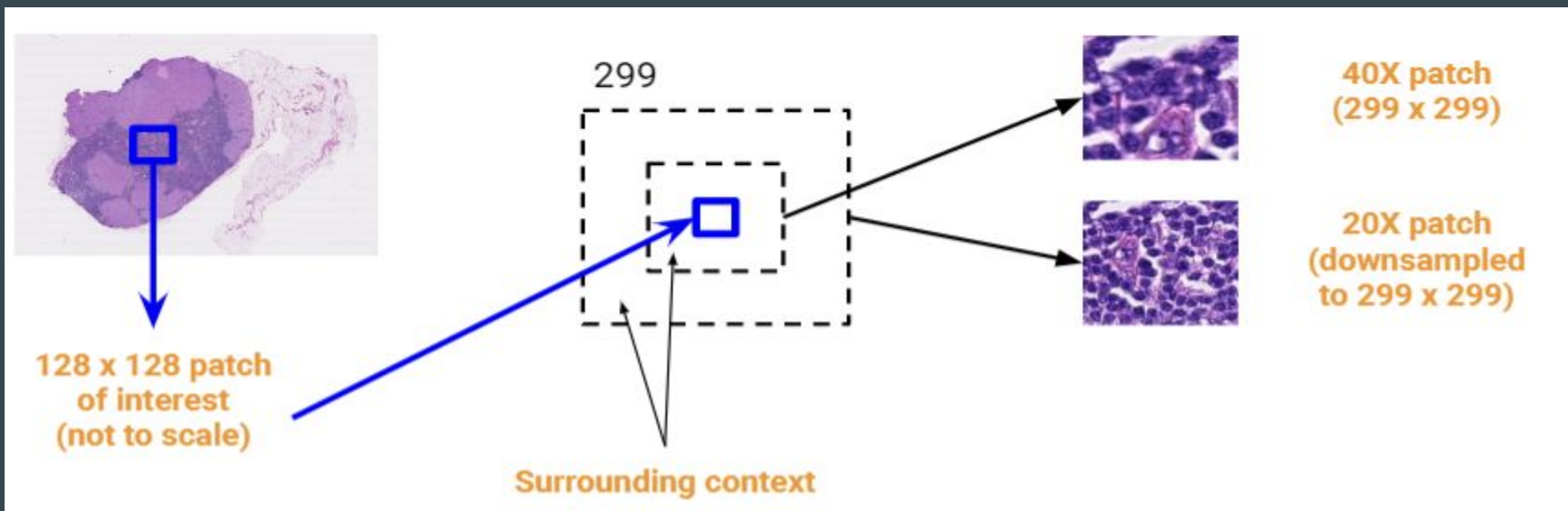
- The task is to predict cancer in gigapixel pathology images.
- Given a collection of data, develop a model that outputs a heatmap showing regions of a biopsy image likely to contain cancer.
- The challenge is from the CAMELYON 16 dataset, whose subset of 21 slides will be used during the entire project for generating the model.

Agenda

- Dataset Preprocessing
 - Load dataset
 - Patching on a zoom level
 - Gray Area removal
 - Centre Alignment in case of multiple zoom levels
- Custom Model
 - One Zoom Level
 - Performance
 - Prediction and maps
- Inception
 - Two Zoom Levels
 - Performance
 - Predictions and heatmaps

Dataset Preprocessing

- Patching (since cancer tissues pertain to small section of the slide)
- Gray Region Removal (for efficiency purposes)
- Centre Alignment (for multiple zoom levels)
- Train Set: 19 slides, Test Set: 2 slides.




Metrics Used for Evaluation

Intersection Over Union (IOU) Score:

- This metric is generally used in image segmentation task for determining the accuracy of the predictor.
- We can leverage it here as well, since we need to determine how our mask corresponds with the ground truth mask.

F1-Score:

- Since, we are dealing with a highly imbalanced dataset, accuracy metric becomes a weak indicator.
- Hence, comes F1-score which is a measure of the precision and recall of the model.


$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

Custom Model with One Zoom Level

- Level = 4
- Patch shape = (32, 32, 3)
- Epochs = 10
- Thresholding at 0.5.
- No Data Augmentation

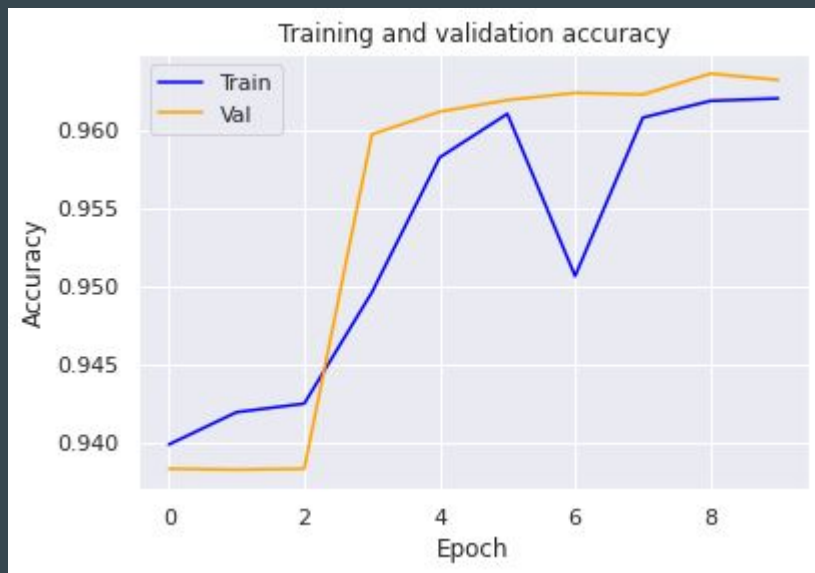
```
[ ]> Model: "sequential"
```

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 30, 30, 16)	448
max_pooling2d (MaxPooling2D)	(None, 15, 15, 16)	0
conv2d_1 (Conv2D)	(None, 13, 13, 64)	9280
max_pooling2d_1 (MaxPooling2D)	(None, 6, 6, 64)	0
dropout (Dropout)	(None, 6, 6, 64)	0
flatten (Flatten)	(None, 2304)	0
dense (Dense)	(None, 1)	2305

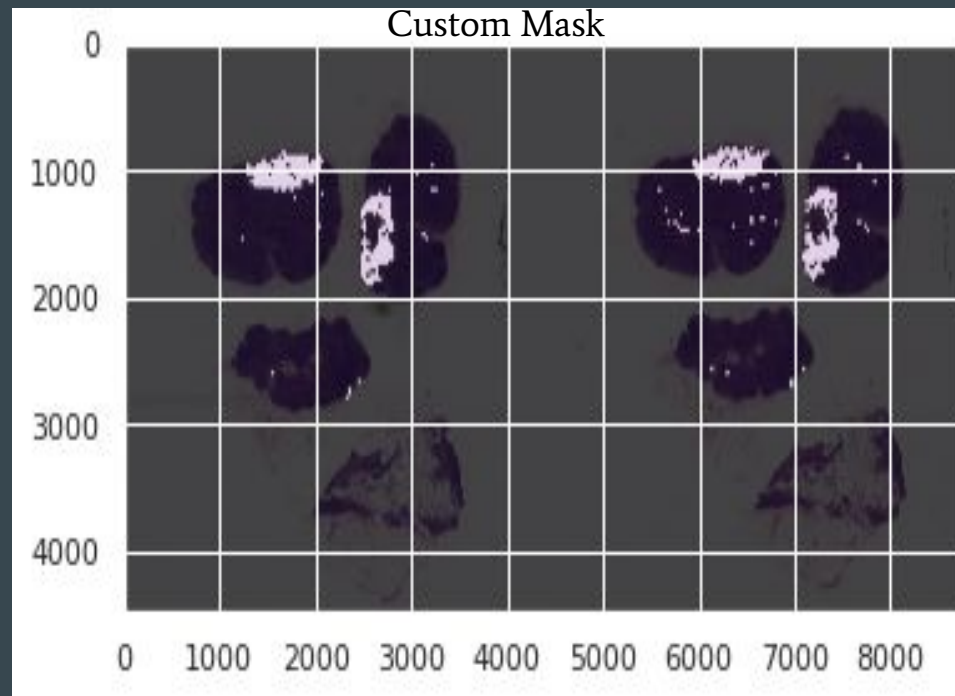
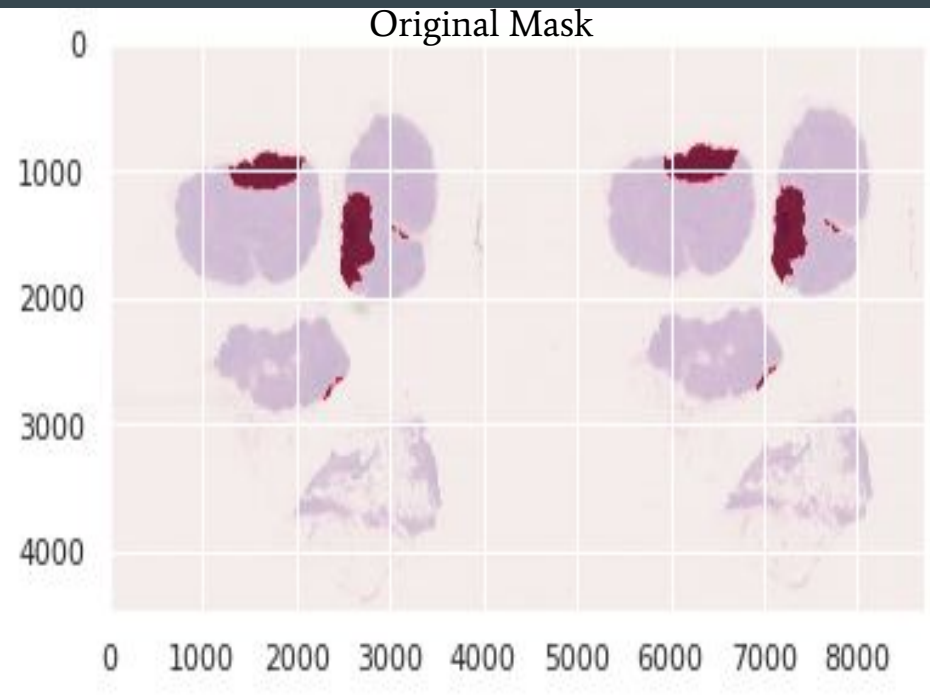
```
Total params: 12,033  
Trainable params: 12,033  
Non-trainable params: 0
```

Custom Model: Performance

- Accuracy and Loss metrics (epochs = 10)
- Intersection Over Union (IOU) measure: 0.57

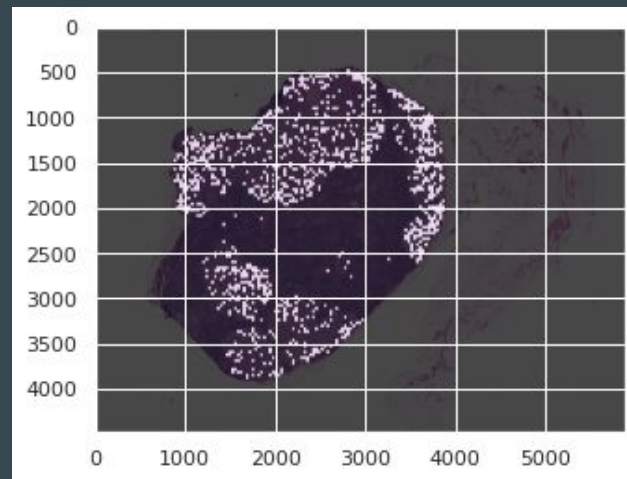
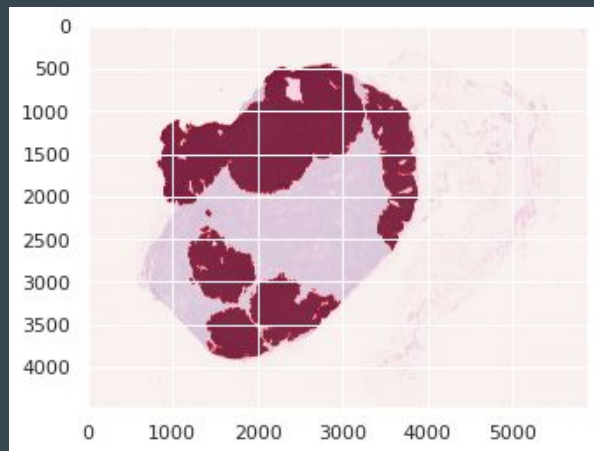


Custom Model: Prediction

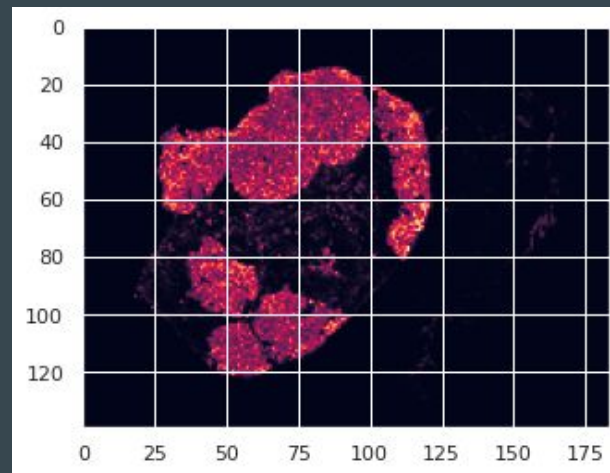


Custom Model: Prediction

With Threshold = 0.5



No Thresholding



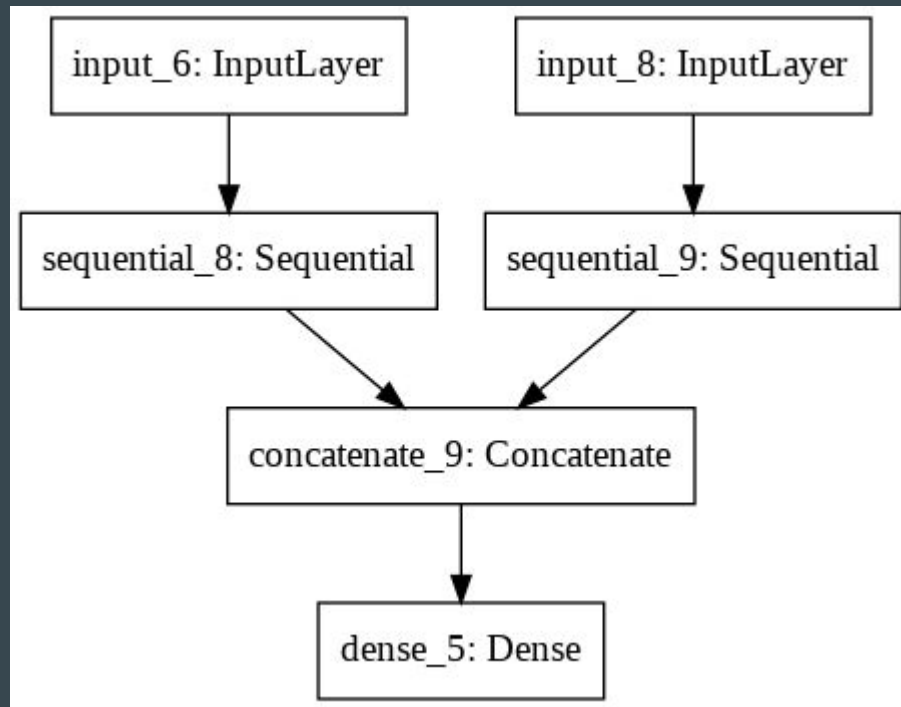
F1-Score and IOU

- Intersection Over Union: 0.57

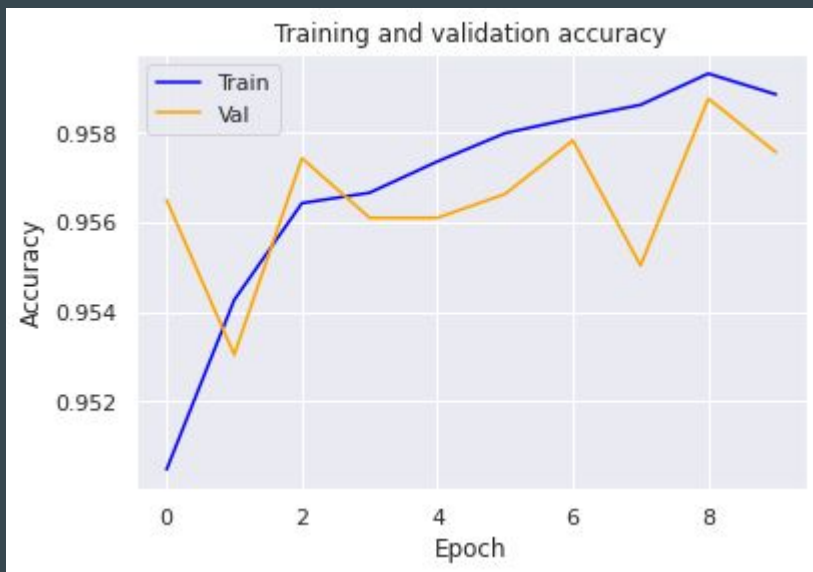
	precision	recall	f1-score	support
0	1.00	0.99	0.99	37481
1	0.59	0.94	0.73	599
accuracy			0.99	38080
macro avg	0.80	0.96	0.86	38080
weighted avg	0.99	0.99	0.99	38080

Inception Model with Two Zoom Levels

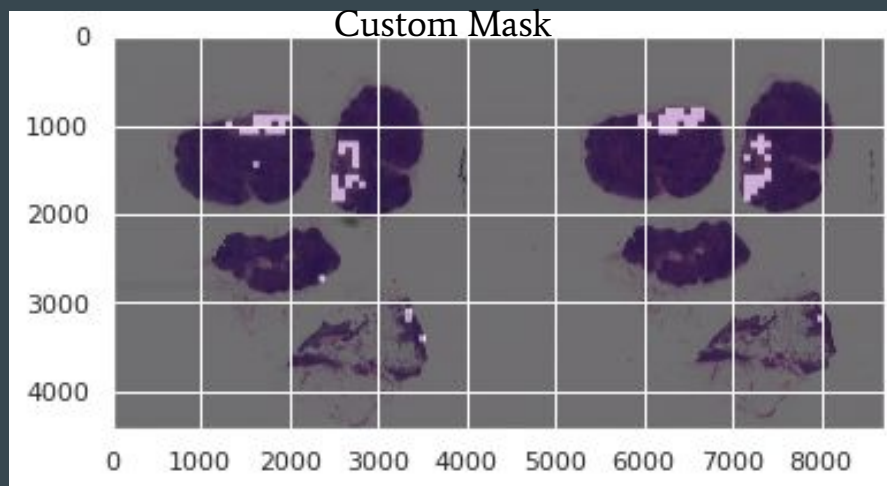
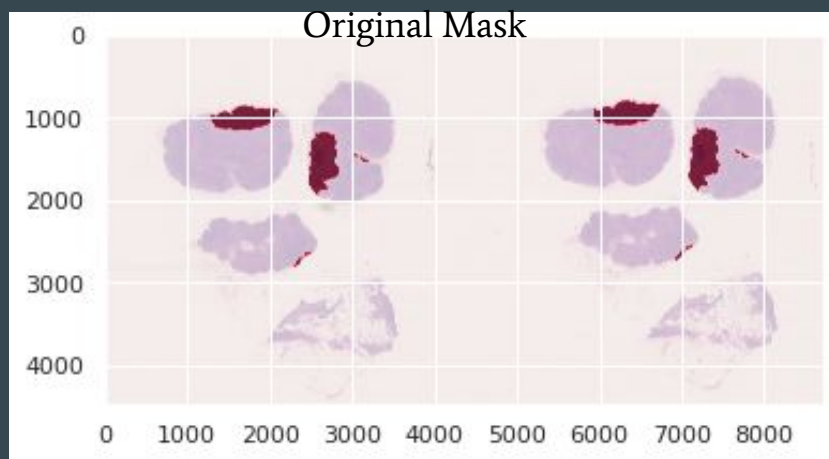
- Level 3 and Level 4
- Patch Shape: (75, 75, 3)
- Epochs = 10
- Thresholding at 0.5
- Data Augmentation



Inception Model: Performance

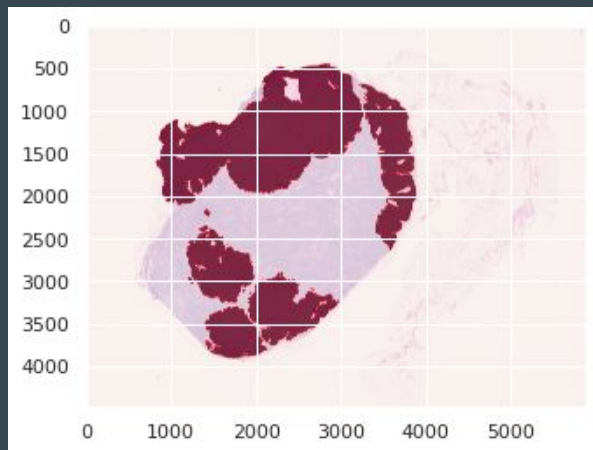


Inception Model: Prediction

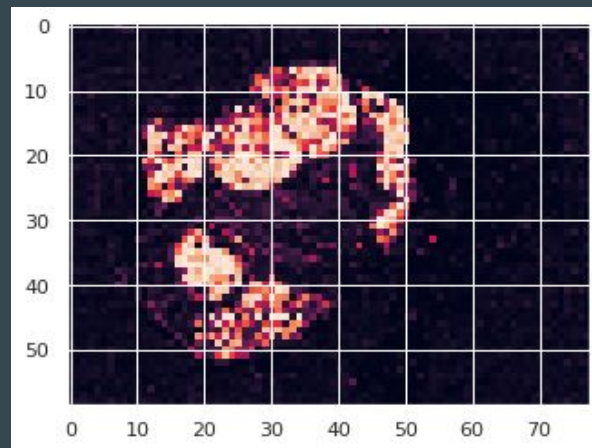
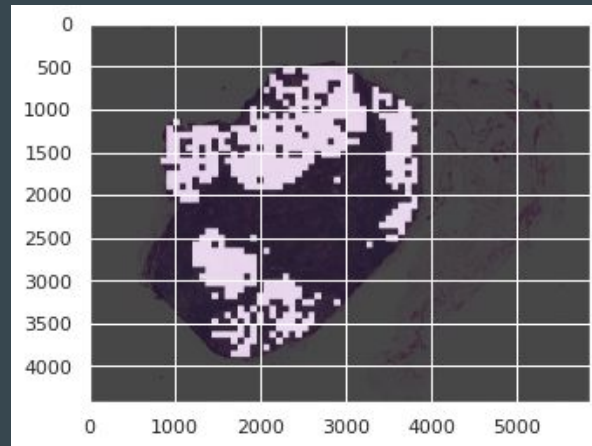


Inception Model: Prediction

With Threshold = 0.5



No Thresholding



F1-Score and IOU

- Intersection Over Union Score: 0.33

	precision	recall	f1-score	support
0	1.00	0.98	0.99	6763
1	0.34	0.94	0.50	81
accuracy			0.98	6844
macro avg	0.67	0.96	0.75	6844
weighted avg	0.99	0.98	0.98	6844

Conclusion

- In terms of accuracy, f1-score and IOU measure, the custom model and InceptionV3 gave similar performance on the 2 slide test set that we had.
- But InceptionV3 performed better, since it was able to achieve the same level of predictability, with only 30065 patches, as compared to 146570 patches for the custom model.
- Hence, even though the performance is similar, InceptionV3 outperforms the custom model in terms of data complexity.

Thank You!