

# *CamelyonAI*

*Automatic Detection and Classification of Breast Cancer Metastases  
for the Camelyon16 Grand Challenge*

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*TRANSCENDING DISCIPLINES, TRANSFORMING LIVES*



**COLUMBIA | ENGINEERING**  
The Fu Foundation School of Engineering and Applied Science



A detailed, high-magnification image of a microchip, showing a complex grid of circuitry with various colored lines (yellow, green, black) and small, intricate components. The background is dark, making the circuitry stand out.

# *Overview and Methodology*

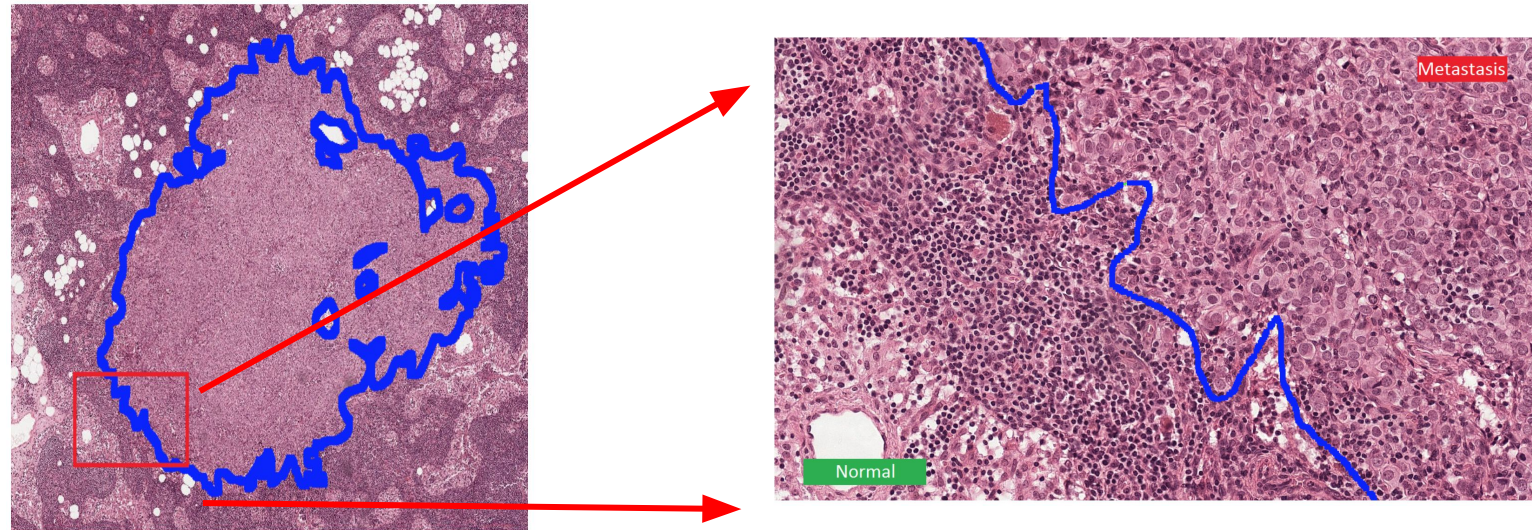
# Camelyon 16 Grand Challenge



**Can a neural network help physicians detect breast cancer metastases?**

The Camelyon16 challenge supplied 400 whole slide images with tumors annotated by expert oncologists.

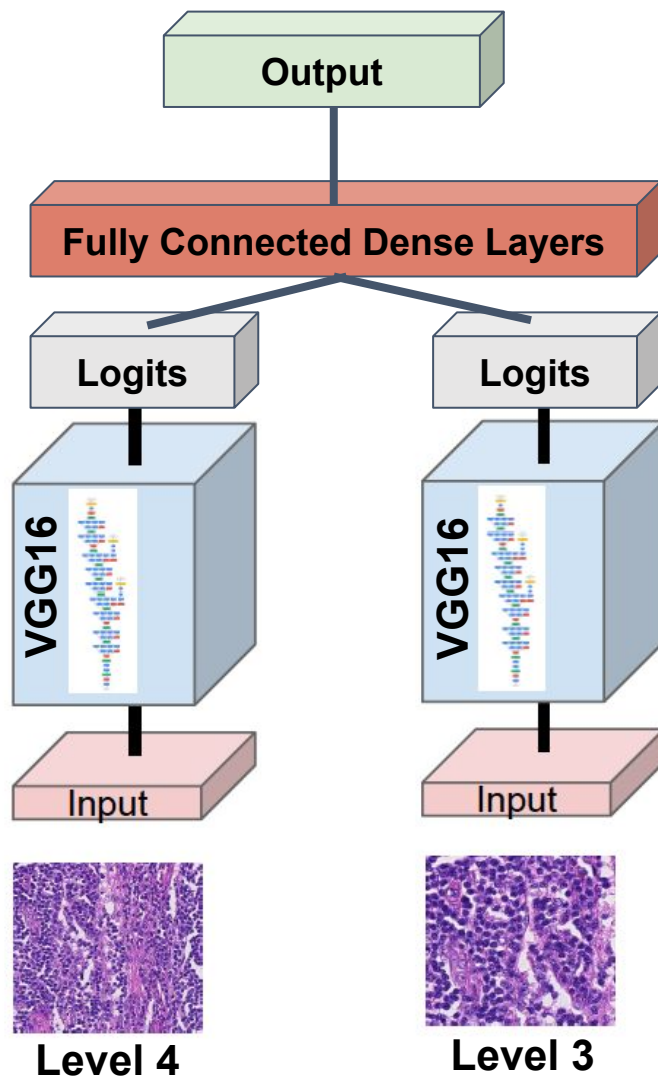
These images and annotations are the neural network inputs, i.e. the groundtruth necessary for training.



<https://camelyon16.grand-challenge.org/>

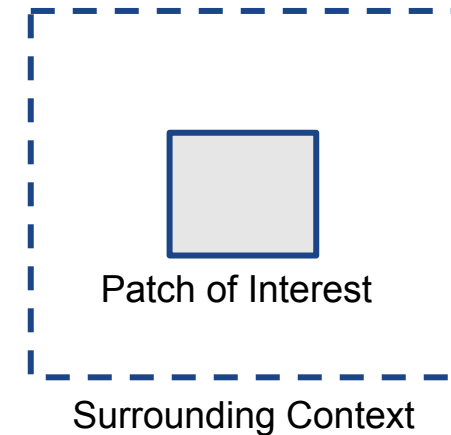


# Parallel Network Architecture



## Why a parallel architecture?

- Image context is important for tumor classification.
- By training on inputs at multiple zoom levels, CNNs can account for both local image characteristics and relevant surrounding features.



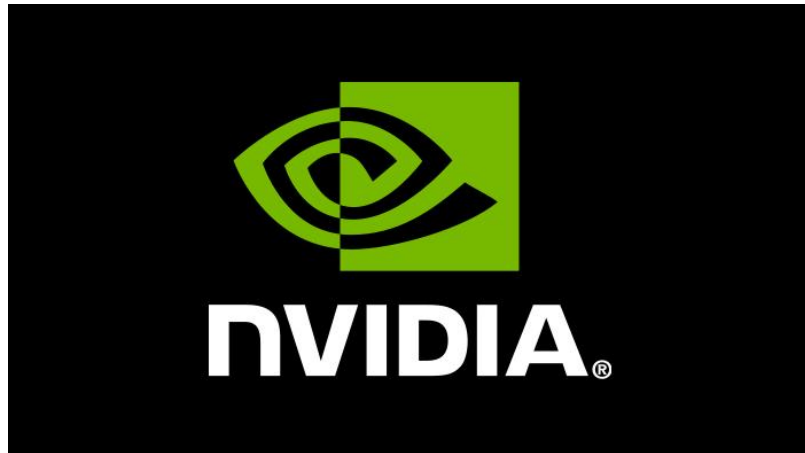
## How is this implemented?

- Model subclassing with tf.keras
  - Two convolutional bases
  - Concatenation of convolutional base output, followed by fully connected dense layers.

<https://arxiv.org/abs/1703.02442>



Google Cloud Platform



## Why not use Google Colab?

- Given the amount of training data and in order to train parallel models, a virtual machine with more than 12 GB RAM is necessary for training.

## Virtual Machine Specifications:

- 8 vCPUs, 52 GB RAM
- 2 NVIDIA Tesla K80s, 24 GB RAM
- 125 GB Disk
- Openslide, TensorFlow-GPU, CUDA, etc.

A detailed, high-magnification image of a microchip, showing a complex grid of circuitry with various colored lines (yellow, green, black) and small, intricate components. The background is dark and textured.

# *Training, Validation, and Testing*

# Model Development

## Evaluation Metric

- F1 Score on level 3 pixel basis

## Data Split

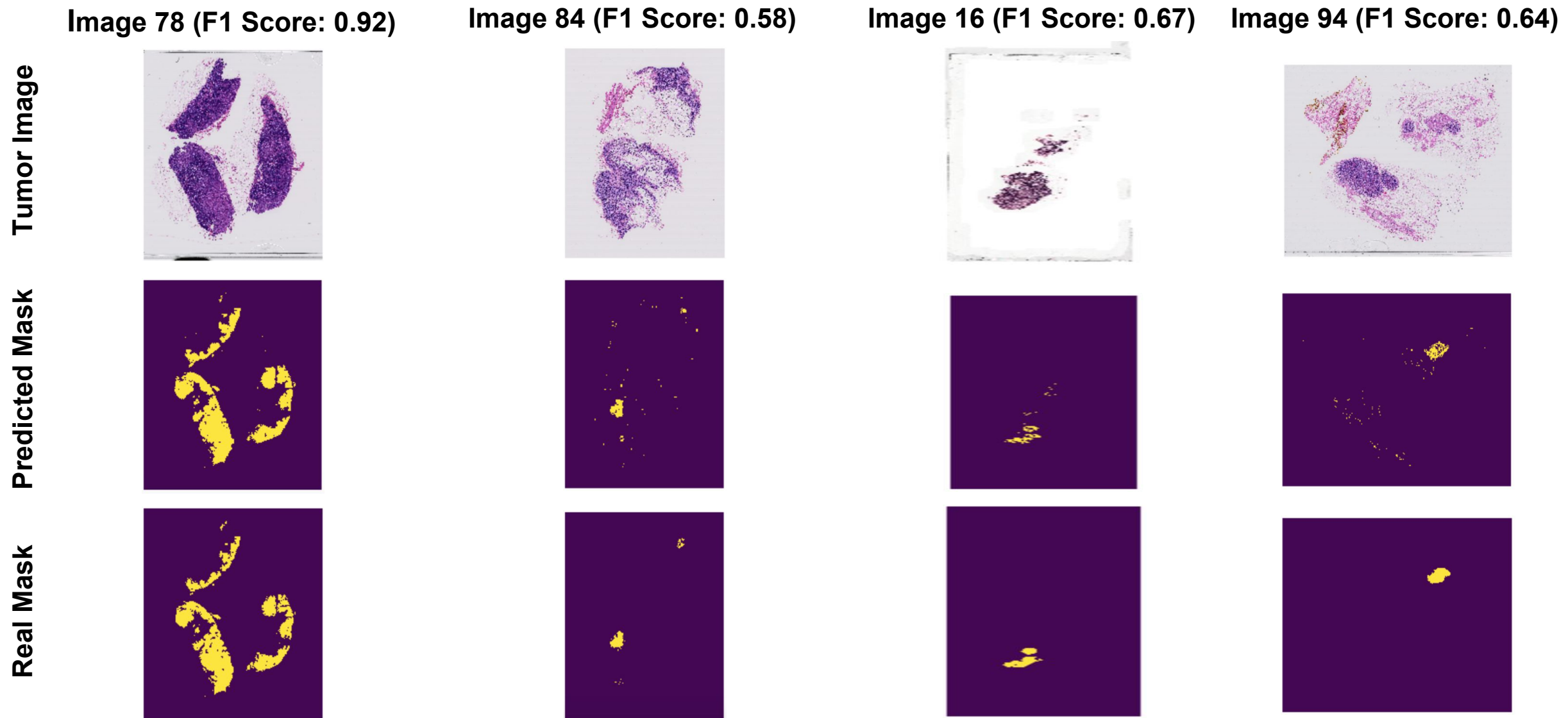
- Training set: 12 random tumors
- Validation set: 4 random tumors
- Test set: 4 random tumors

## Model Tuning Process

1. Train model on training set
2. F1 score on validation set
3. Repeat steps 1 & 2 on potential models
4. Select best model (M4) - train on training+validation set
5. Evaluate on test set

	Model				
Features	Baseline	M1	M2	M3	M4
Image Levels	3	3,4	3,4	3,5	3,4
Conf. Threshold	70%	70%	70%	70%	85%
Conv. Base	VGG16	VGG16	Xception	VGG16	VGG16
Mean F1 Score	0.56	0.64	0.61	0.57	0.65

# Optimized Model Performance -- Model M4





A detailed, high-magnification image of a microchip, showing a complex grid of circuitry with various colored lines (yellow, green, black) and small, intricate components. The word "Conclusions" is centered over this image in a white, italicized serif font.

# *Conclusions*

# Primary Takeaways

## Conclusions:

- Parallel networks allow for more accurate tumor detection.
- VGG performs better than Xception as a convolutional base in this scenario.
- Training on slides levels 3 and 4 results in the highest accuracy.
- Overprediction can be mitigated by adjusting the confidence threshold.

## Future Work:

- Lower level images (1 & 2)
- Additional parallel models
- Larger training and validation sets
- Higher granularity model tuning
  - Epoch count
  - Alternative convolutional base models
  - Image augmentation
  - Number/size of dense layers after transfer learning, before output

[Github Repository](#)

Thank you!  
Questions?