IEEE - ISBI 2021
International Symposium on Biomedical Imaging

Leveraging Global Diagnosis for Tumor Localization in Dynamic Cell Imaging of Breast Cancer Tissue Towards Fast Biopsying

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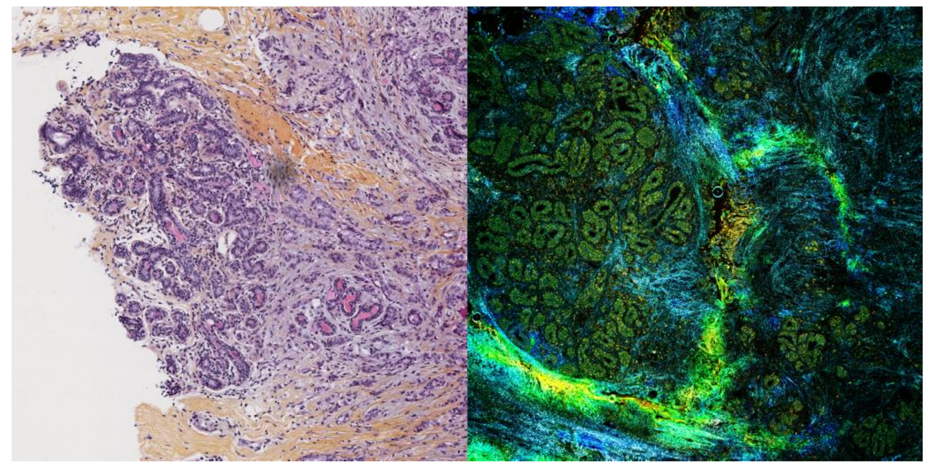
CONTEXT

Diagnosis at the point-of-care for **biopsies** & **surgical margins** :

- ✓ fast **non-invasive imaging** with *Dynamic Full Field Optical Coherence Tomography* (aka *Dynamic Cell Imaging* - DCI) technique offering 10 min/cm^2 acquisition speed and 1µm resolution in 3D;
- ✓ immediate **automated diagnosis** and **localization** of malignancy through *AI-based algorithm.*



Normal breast lobule appearance in **H&E Histology** *vs.* **DCI**

LightCT Scanner by LLTech

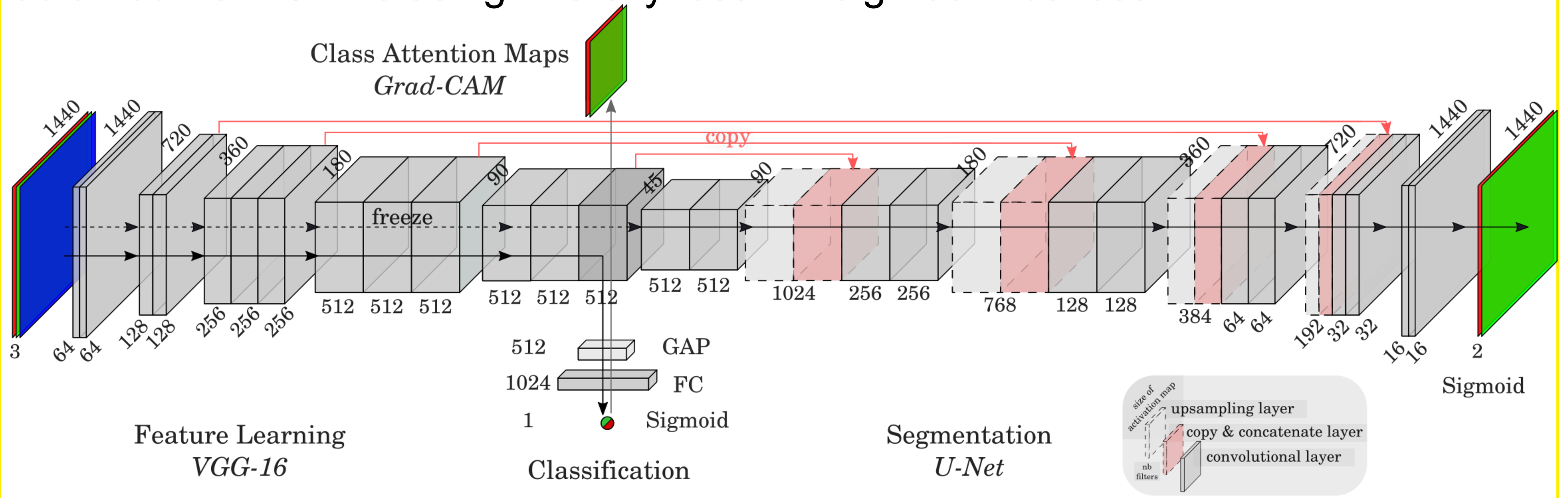
METHOD

Feature Learning via Classification :

- VGG-16 *backbone* (pre-trained, ~15M params) + narrow *bottleneck* (Global Average Pooling) + shallow classifier to enforce generalization.
- Minimize weighted binary cross-entropy loss with SGD (lr=1e-4, momentum=0.8, batch=3) until convergence (~100 epochs).

Class Activation Maps : modified Grad-CAM accounting for both positive and negative gradients, i.e. reveal input areas accounting for and against tumor class.

Self-supervised Segmentation : train U-Net decoder on segmentation masks obtained from CAMs using Tversky loss ≡ weighted Dice loss.

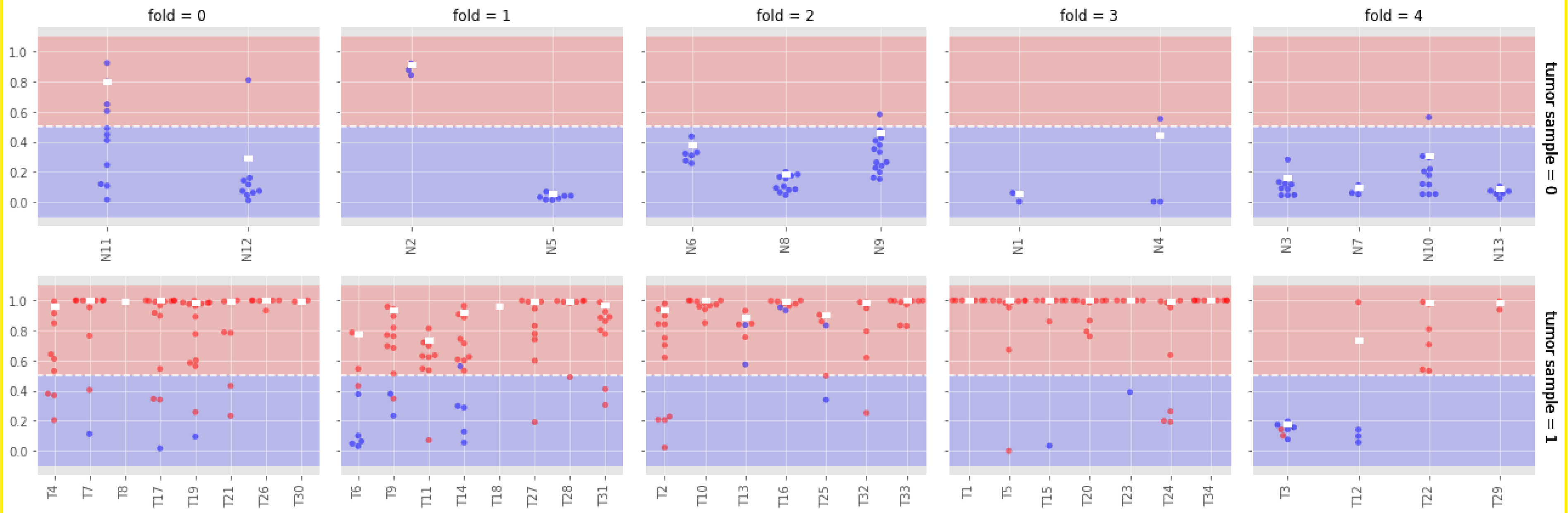


Streamlined architecture : U-Net with VGG-16 backbone and Grad-CAM computation

DATASET

- 33 *patients* who have undergone *partial or total breast ablations*
- 47 *samples* (34 pathological, 13 normal) from surgical waste
- 396 DCI fields-of-view (260 with tumor, 136 normal)

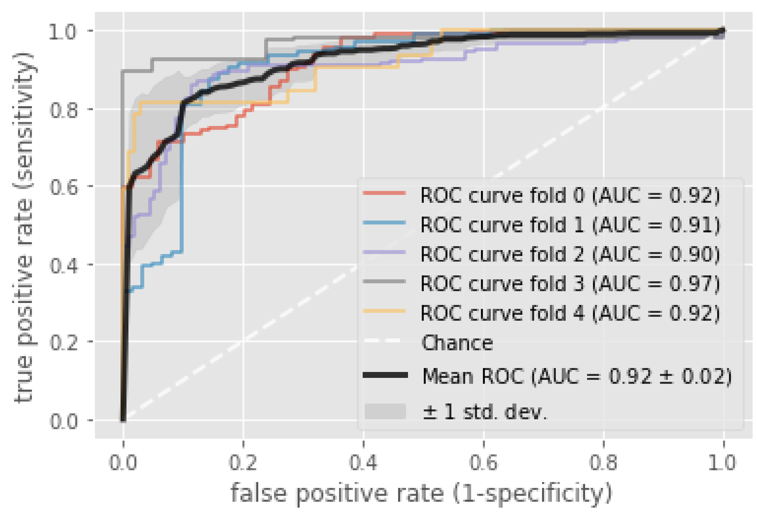
QUANTITATIVE RESULTS



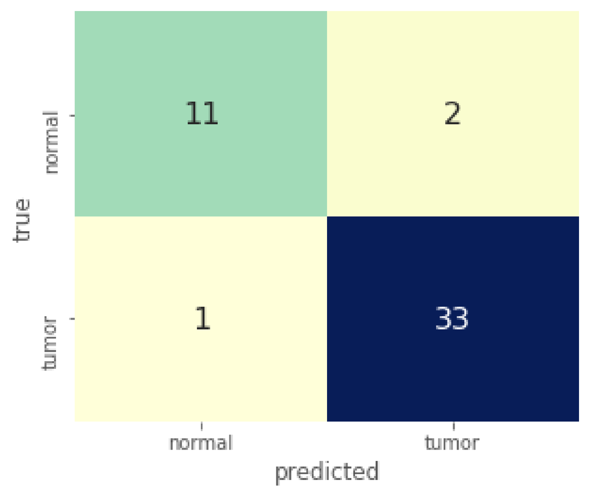
Prediction of FOVs per sample per fold : x-axis = sample, y-axis = tumor prediction, point = FOV, top figs = healthy samples, bottom figs. = cancerous samples, vertical figs. = folds

	Accuracy	Sensitivity	Specificity	F1-Score	ROC AUC
per FOV	89 ± 4 %	88 ± 4 %	86 ± 6 %	90 ± 3 %	0.92 ± 0.02
per SAMPLE	94 ± 5 %	95 ± 10 %	80 ± 24 %	95 ± 5 %	0.96 ± 0.05

5-fold cross-validation **metrics** (average ± standard deviation)

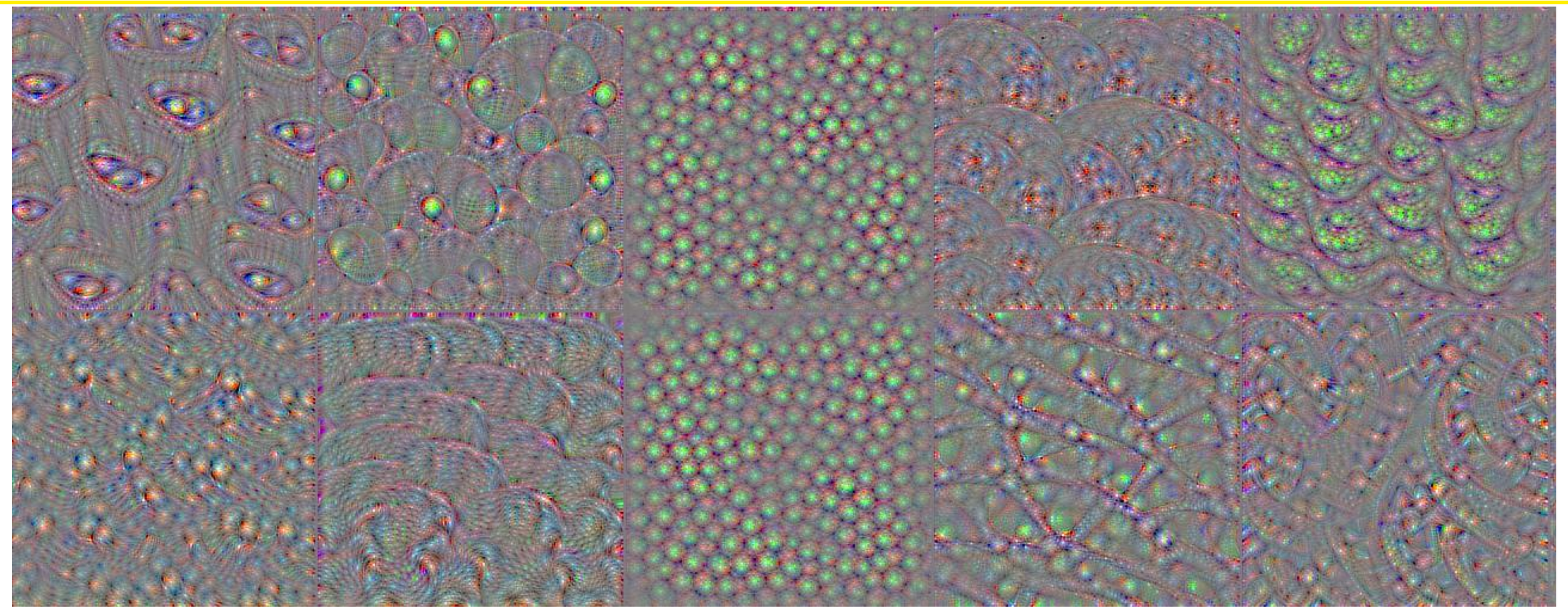


FOV-wise **ROC** curves over CV folds

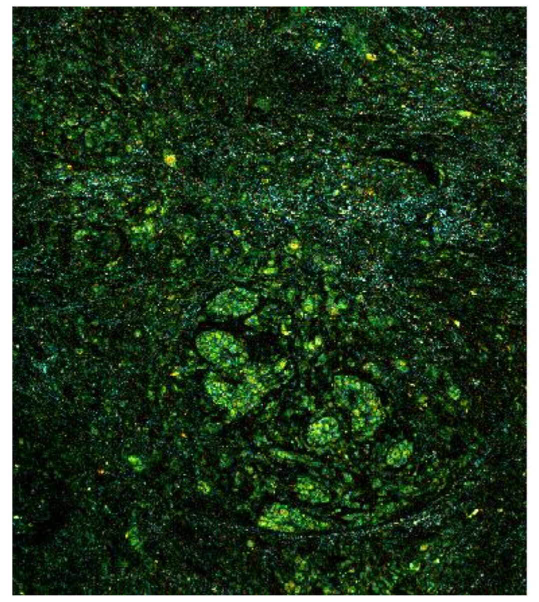


Confusion matrix aggregated sample-wise over all CV folds

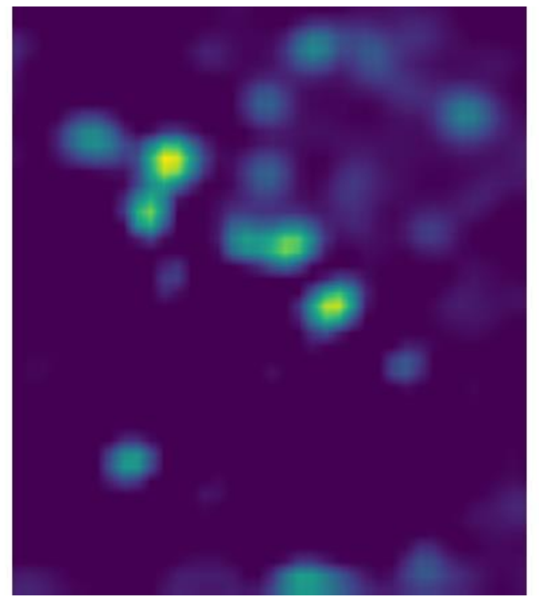
QUALITATIVE RESULTS



Example of some learned ***filters*** in the last convolutional layer showing different **cell sizes, shapes and organization**



DCI crop of FOV correctly classified as tumoral with **97%** probability



Tumor-positive *activation map* highlighting **isolated cancer cells**

Tumor-negative *activation map* highlighting **healthy breast lobule**

CONCLUSION

- ✓ **High confidence** breast tumor **classification** through *high performance metrics* and *qualitative assessment.*
- ✓ **Tumor localization** from training on global tumor presence only.
- ✓ **Classification** and **segmentation** *streamlined together* for easy model deployment.

REFERENCES

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