

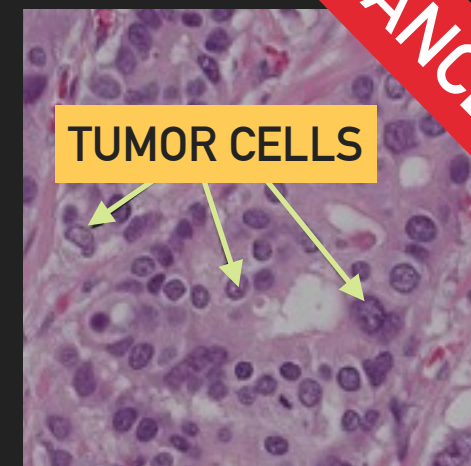
MULTI-LOSS CONVOLUTIONAL NETWORKS FOR GLAND ANALYSIS IN MICROSCOPY

AÏCHA BENTAIEB, **JEREMY KAWAHARA**, GHASSAN HAMARNEH

ISBI 2016, SPECIAL SESSION IN DEEP LEARNING FOR MEDICAL IMAGING

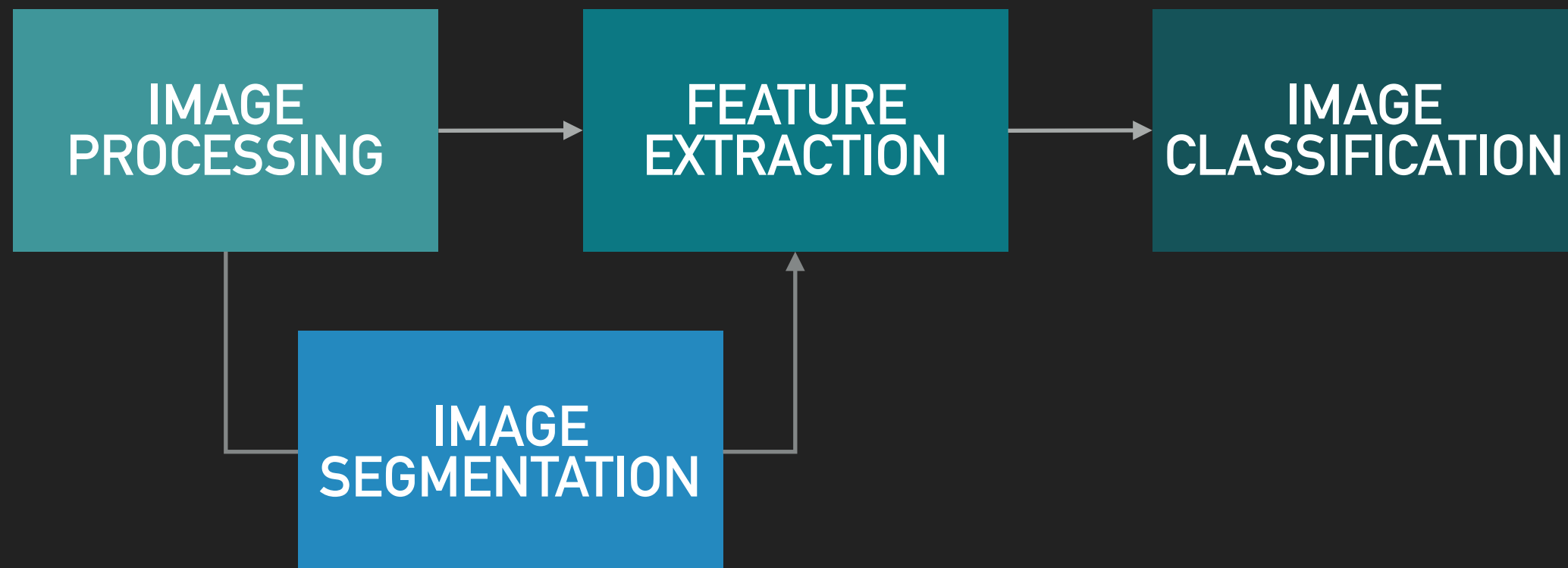
CANCER DIAGNOSIS

- ▶ Pathologists' diagnosis involves **simultaneous** feature **identification** and tumor **classification**.



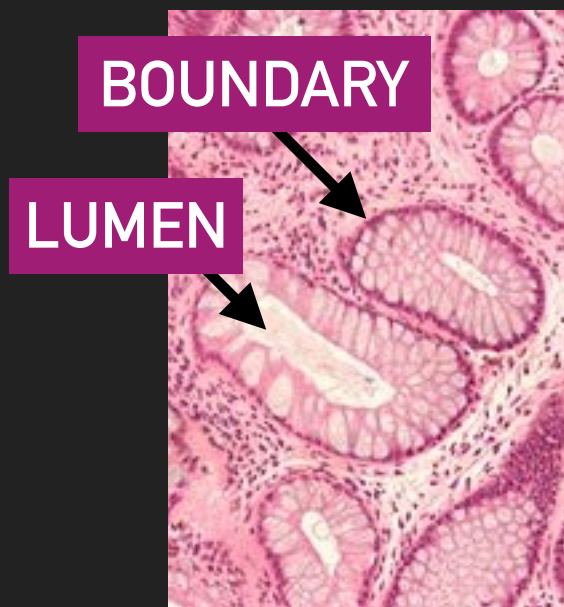
AUTOMATIC CANCER DIAGNOSIS

- ▶ Automatic cancer diagnosis often involves **independent** segmentation and classification steps.



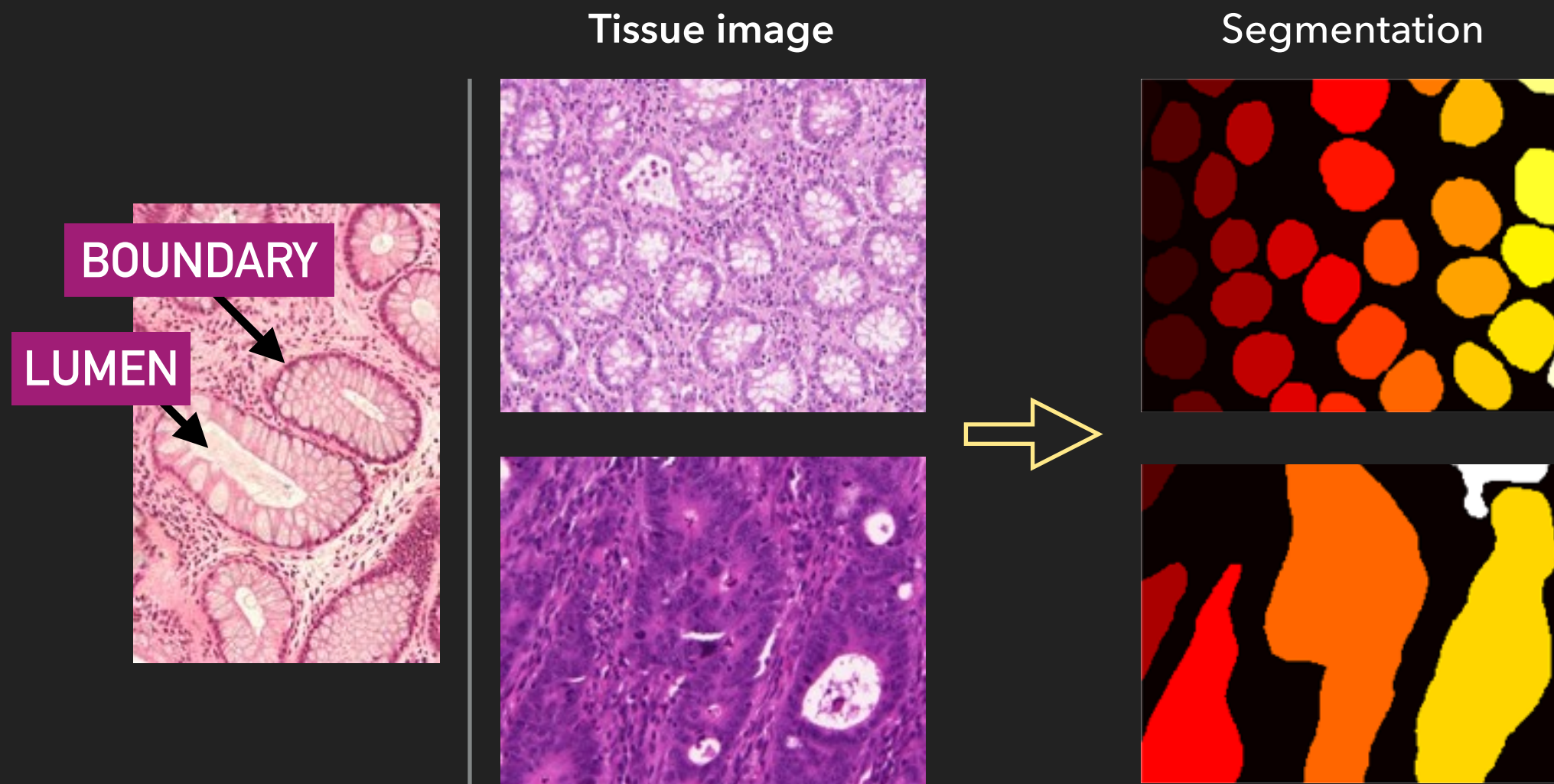
EXAMPLE: GLAND ANALYSIS FOR CANCER DIAGNOSIS

- ▶ **Glands** are reliable bio-markers for different types of adenocarcinoma: **colon**, breast, prostate, etc.



GLAND ANALYSIS FOR CANCER DIAGNOSIS

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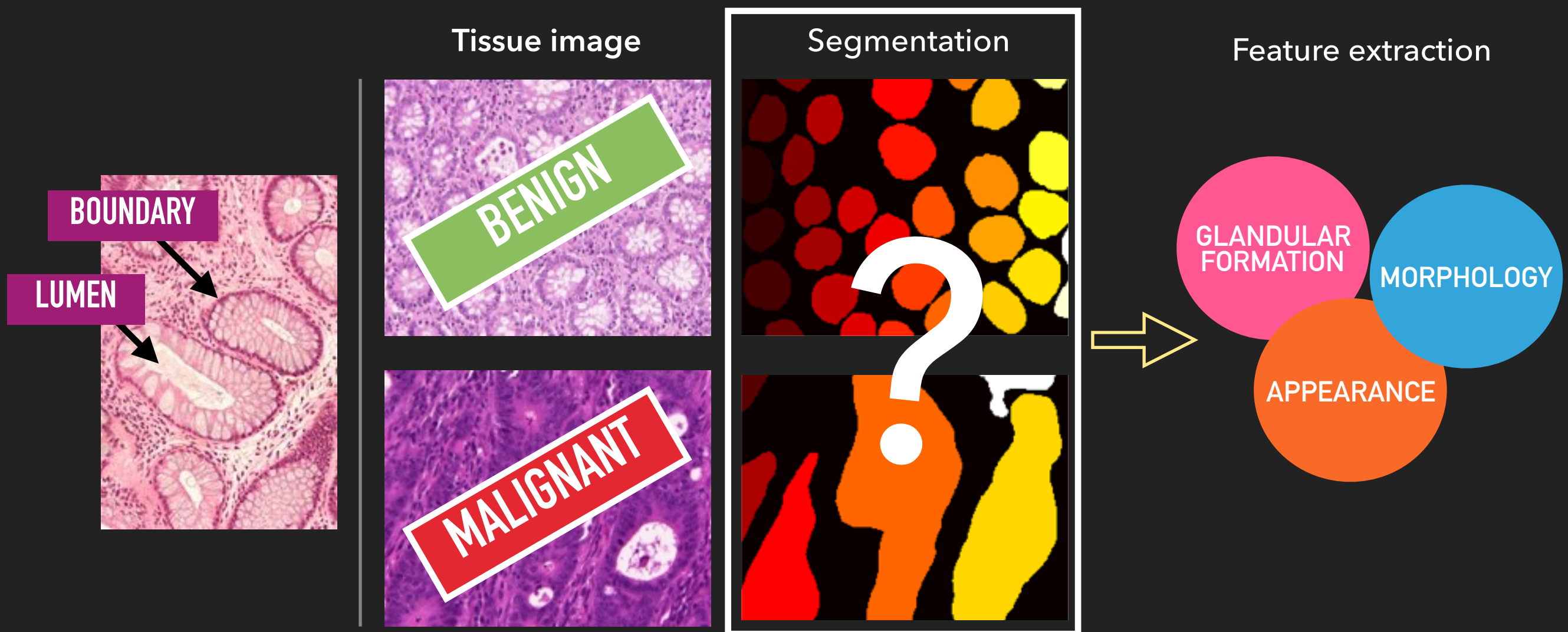
GLAND ANALYSIS FOR CANCER DIAGNOSIS

- ▶ **Glands** are reliable bio-markers for different types of adenocarcinoma: **colon**, breast, prostate, etc.



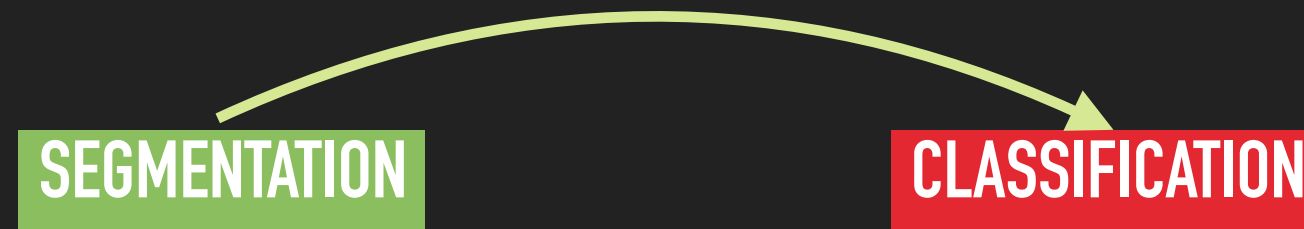
GLAND ANALYSIS FOR CANCER DIAGNOSIS

- ▶ Should the **class** information influence the **segmentation** ?



JOINT CLASSIFICATION-SEGMENTATION

- ▶ Classification requires segmentation-based features ...

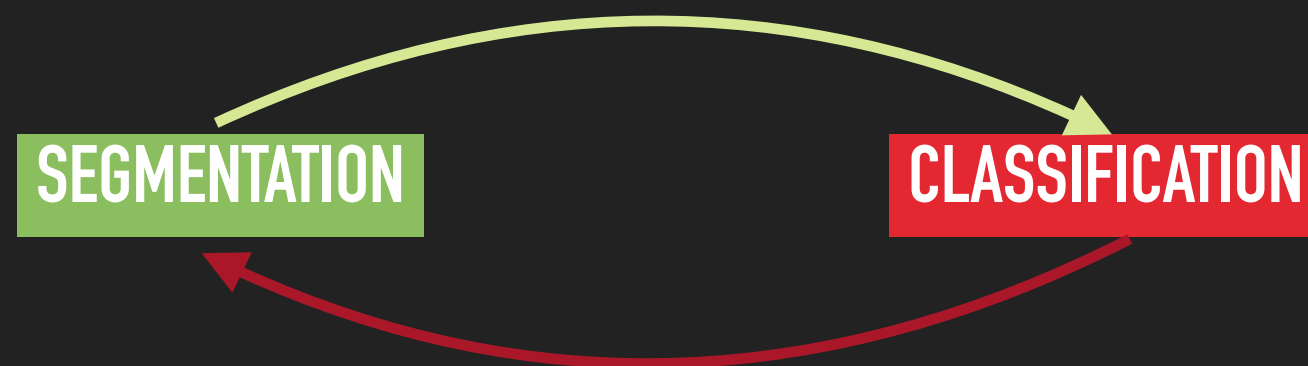


- ▶ but generally, segmentation techniques does not involve knowledge of the class ...

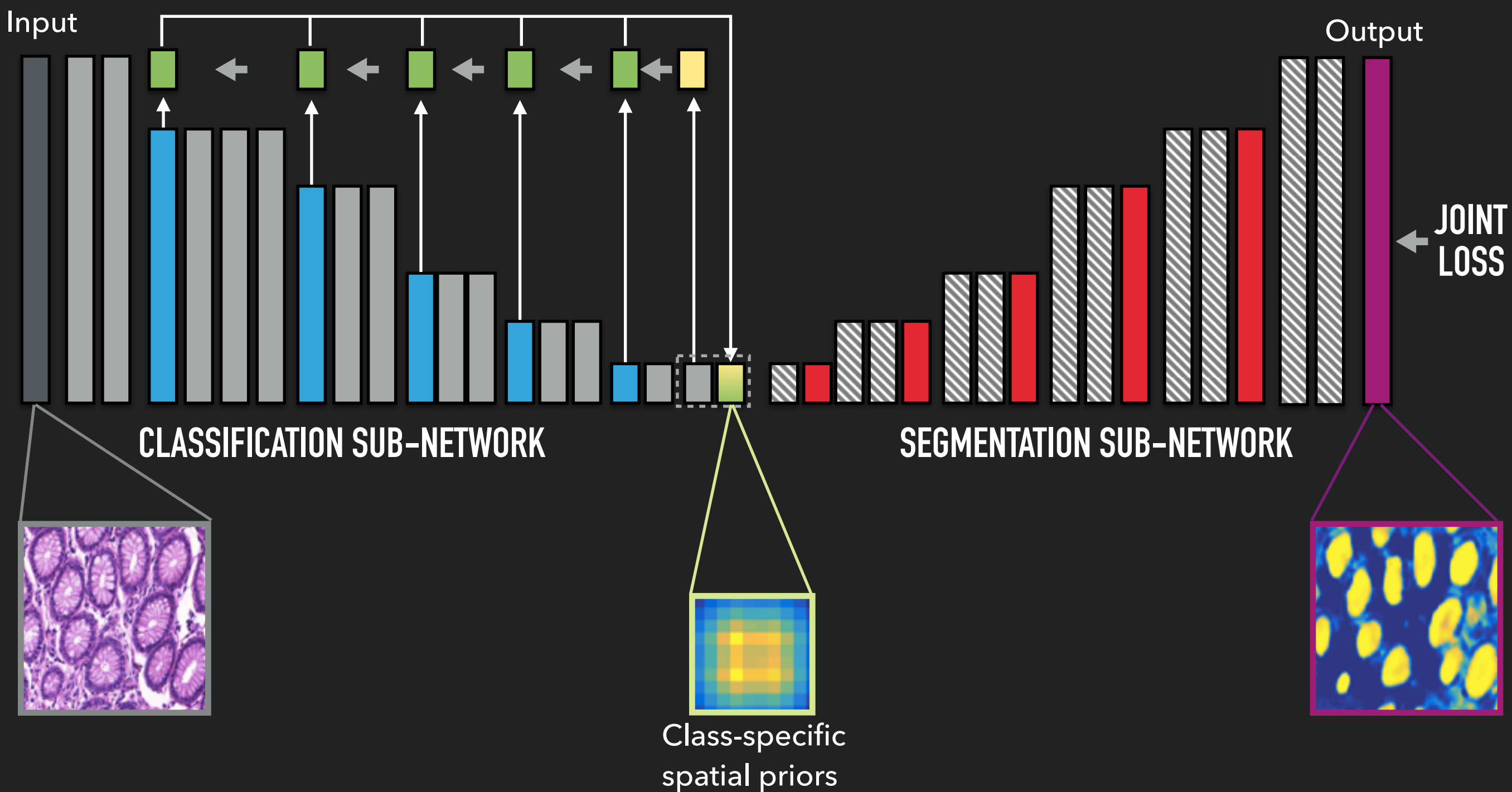


JOINT CLASSIFICATION-SEGMENTATION

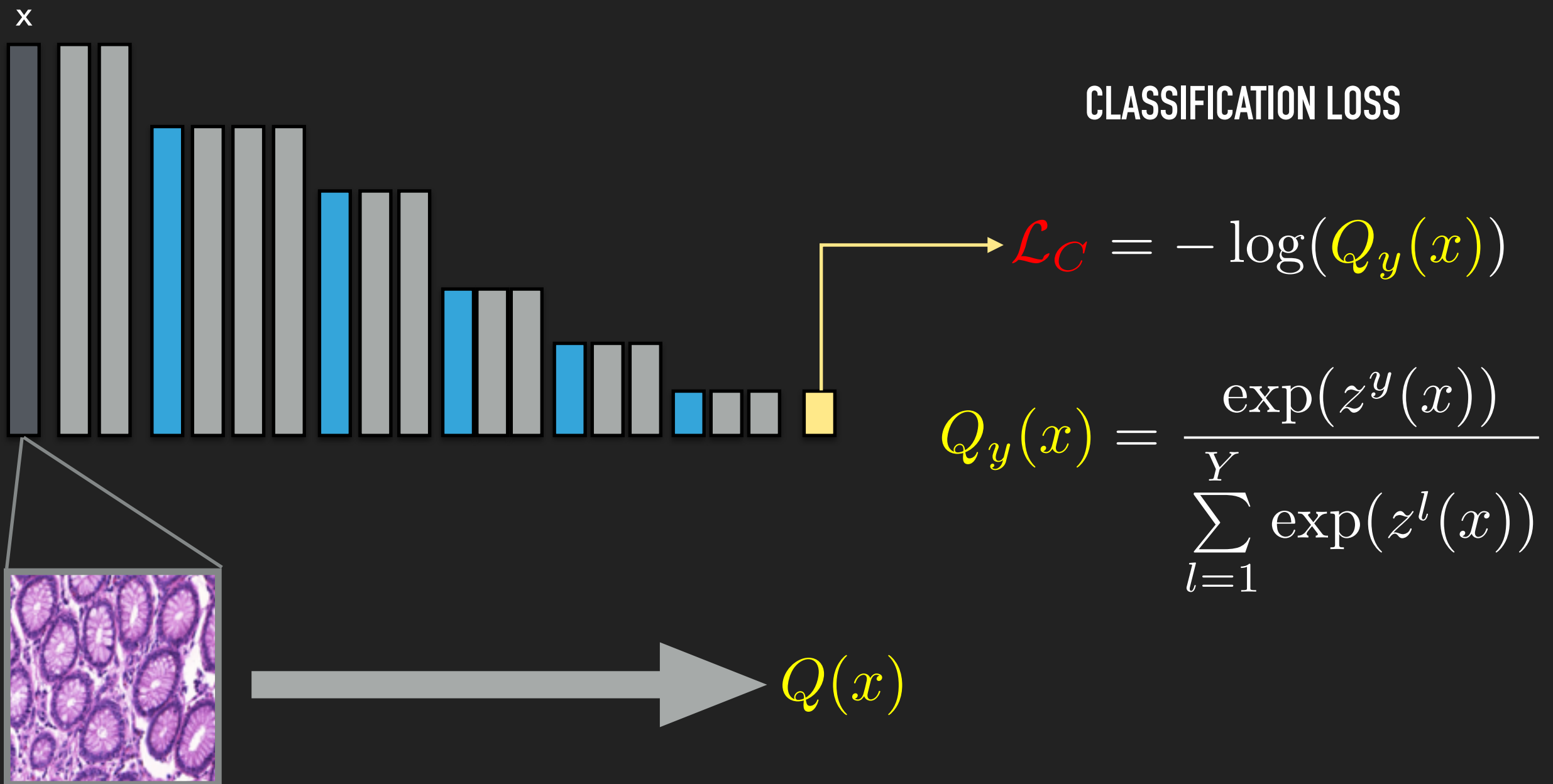
- ▶ We pose the problem of automatic tissue diagnosis as the **joint task** of segmentation and classification.
- ▶ **Goal**: train an end-to-end system to jointly optimize the classification and segmentation predictions.
- ▶ Using a deep learning model.



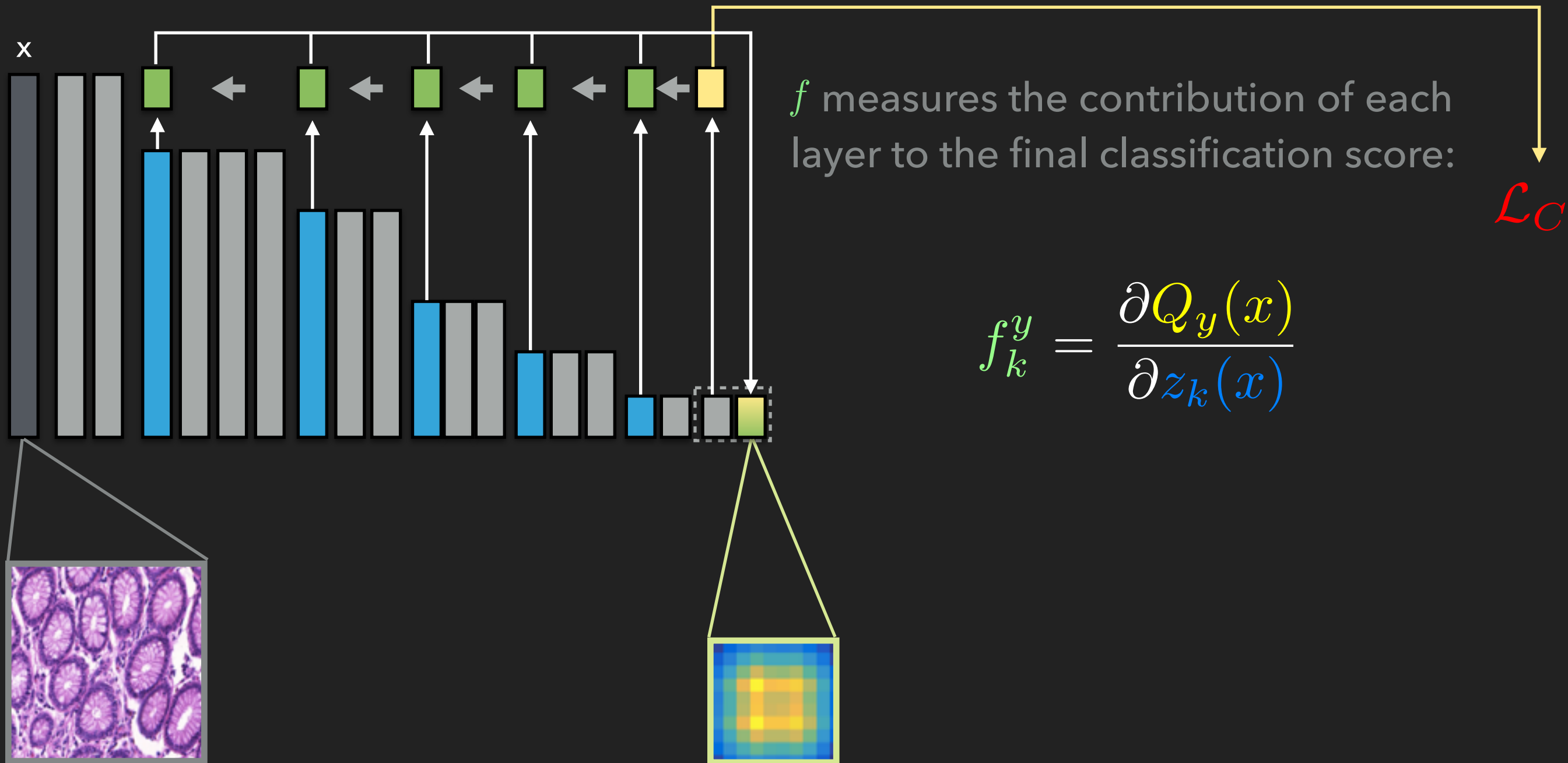
HYBRID CLASSIFICATION-SEGMENTATION NETWORK



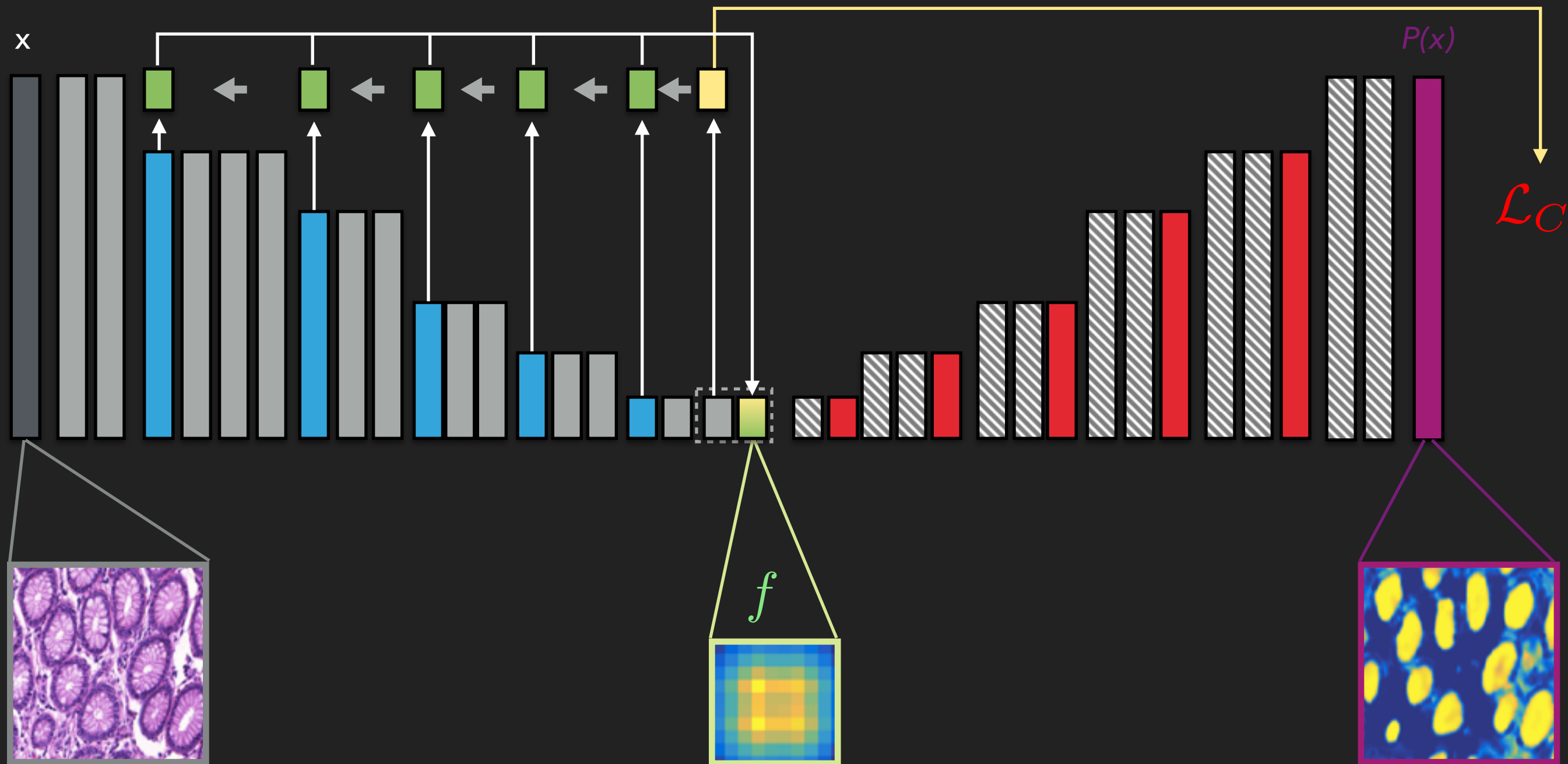
CLASSIFICATION SUB-NETWORK



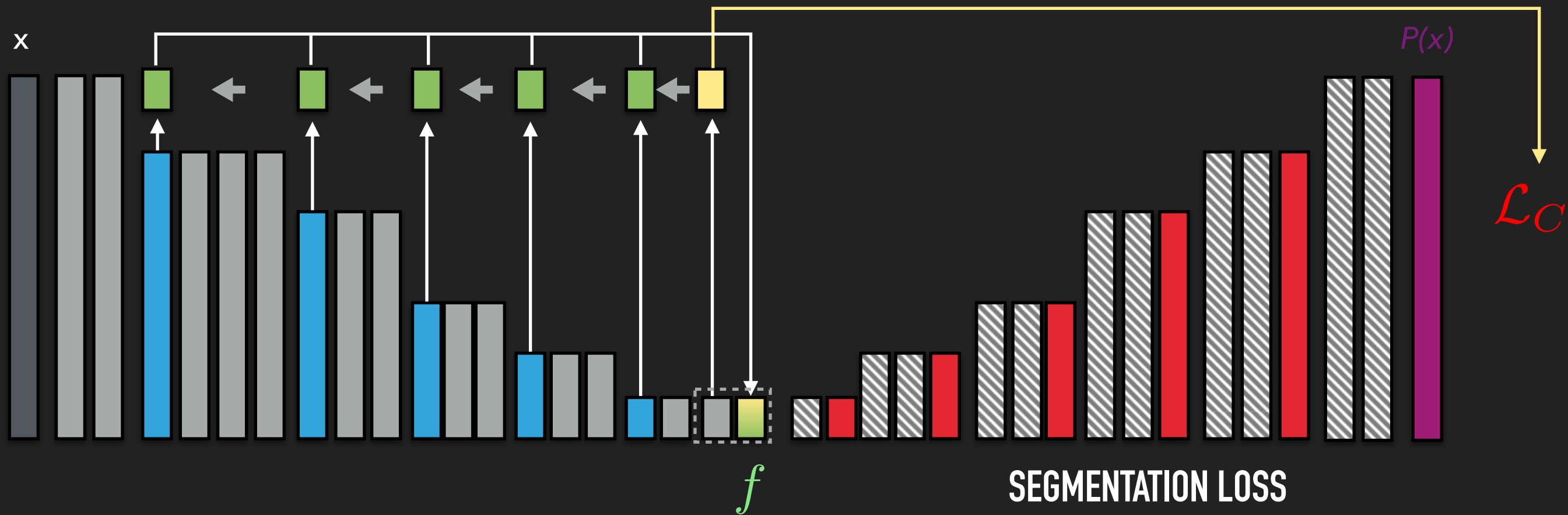
CLASS-SPECIFIC SPATIAL PRIORS



FULLY CONVOLUTIONAL SEGMENTATION NETWORK

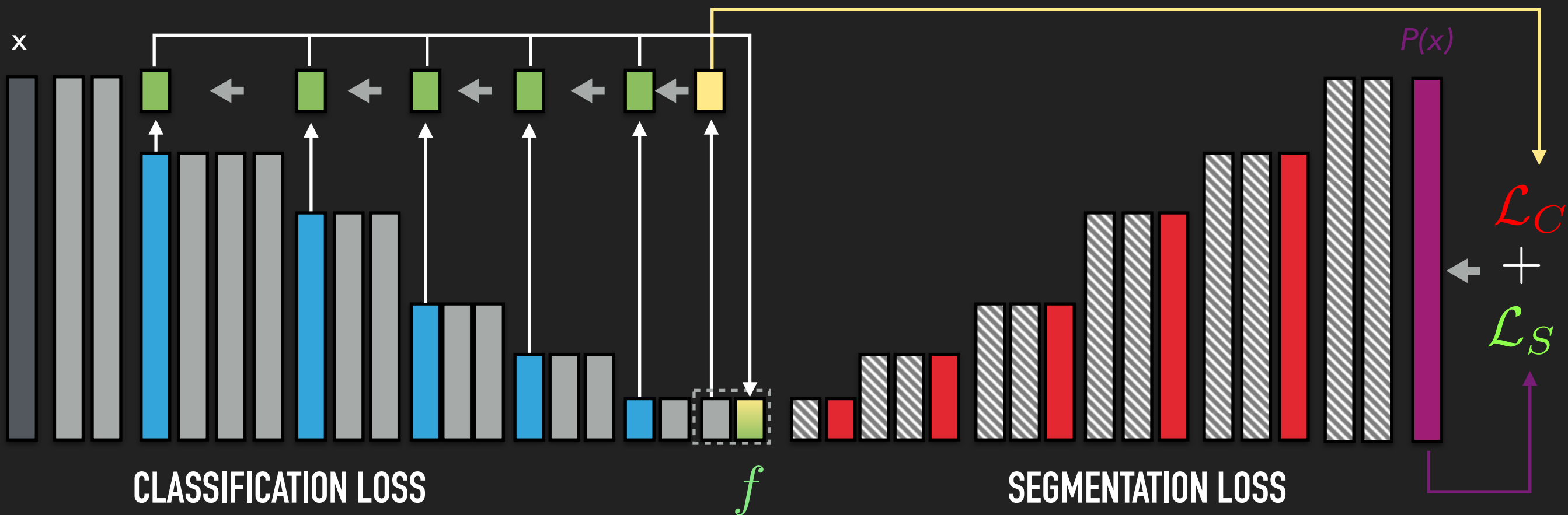


WEIGHTED SEGMENTATION LOSS



$$\mathcal{L}_S = - \sum_{j=1}^{\Omega} S_j f_j^g (\log P_g(x_j)) + (1 - S_j) f_j^b \log(P_b(x_j))$$

MULTI-LOSS NETWORK



$$\mathcal{L}_C = -\log(Q_y(x))$$

$$\mathcal{L}_S = -\sum_{j=1}^{\Omega} S_j f_j^g (\log P_g(x_j))$$

$$\text{Proposed Loss} = \mathcal{L}_C + \mathcal{L}_S$$

$$+(1 - S_j) f_j^b \log(P_b(x_j))$$

EXPERIMENTS

▶ Dataset:

- ▶ GLaS gland segmentation challenge, MICCAI 2015 [1].
- ▶ 85 training images: 37 Benign, 48 Malignant.
- ▶ 80 test images: 37 Benign, 43 Malignant.

▶ Model training:

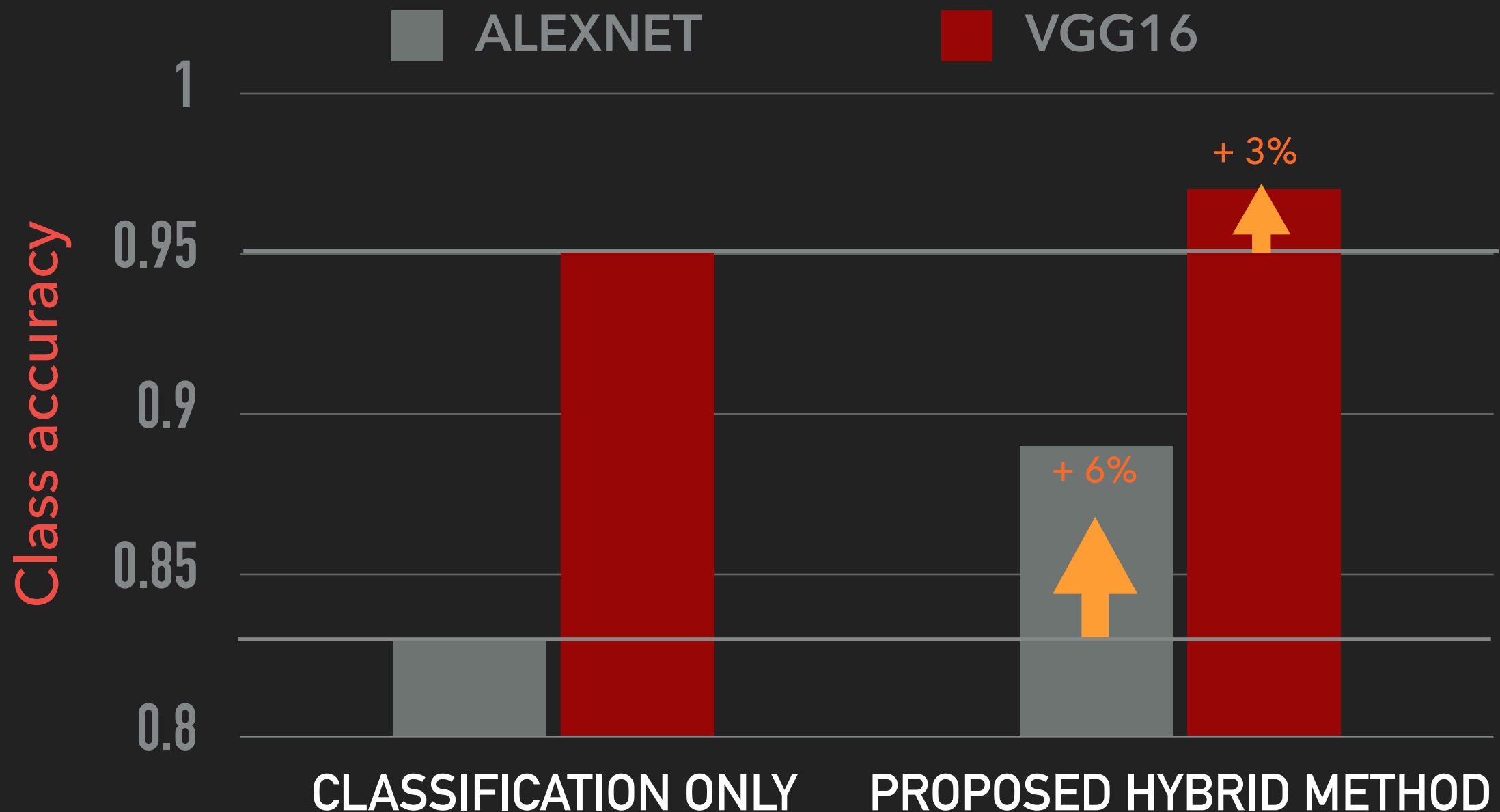
- ▶ Sequential training: 1) Classifier 2) Segmentation 3) Joint fine-tuning.
- ▶ Stochastic Gradient Descent optimization.
- ▶ Implemented in Caffe [2].

[1] Sirinukunwattana et al. arXiv:1603.00275 (2016).

[2] Jia et al. arXiv:1408.5093 (2014).

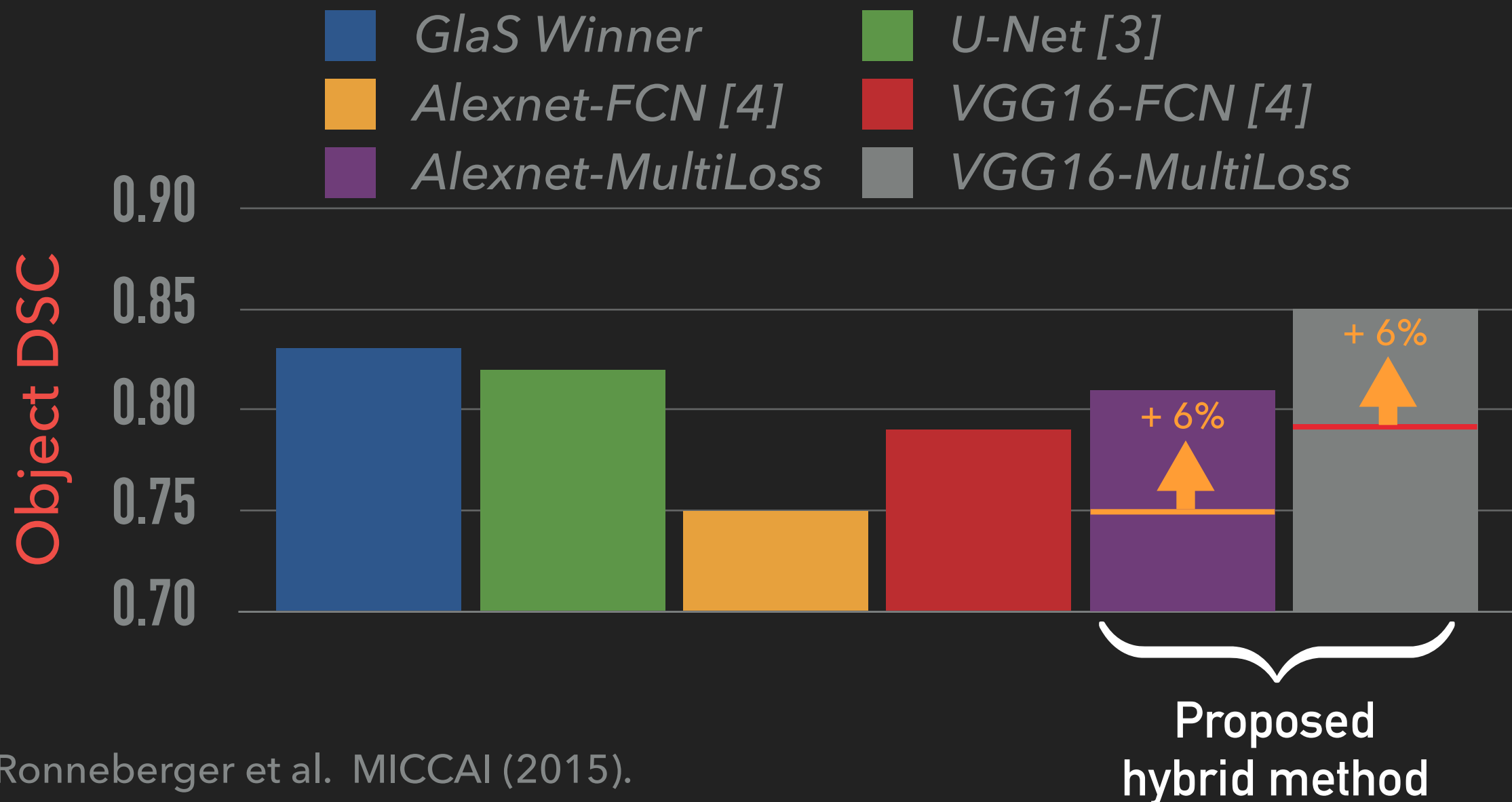
CLASSIFICATION ACCURACY

Our hybrid classification-segmentation approach increases the classification accuracy up to **6%**



SEGMENTATION RESULTS

Using class-specific priors increases the segmentation Dice by **6%**.

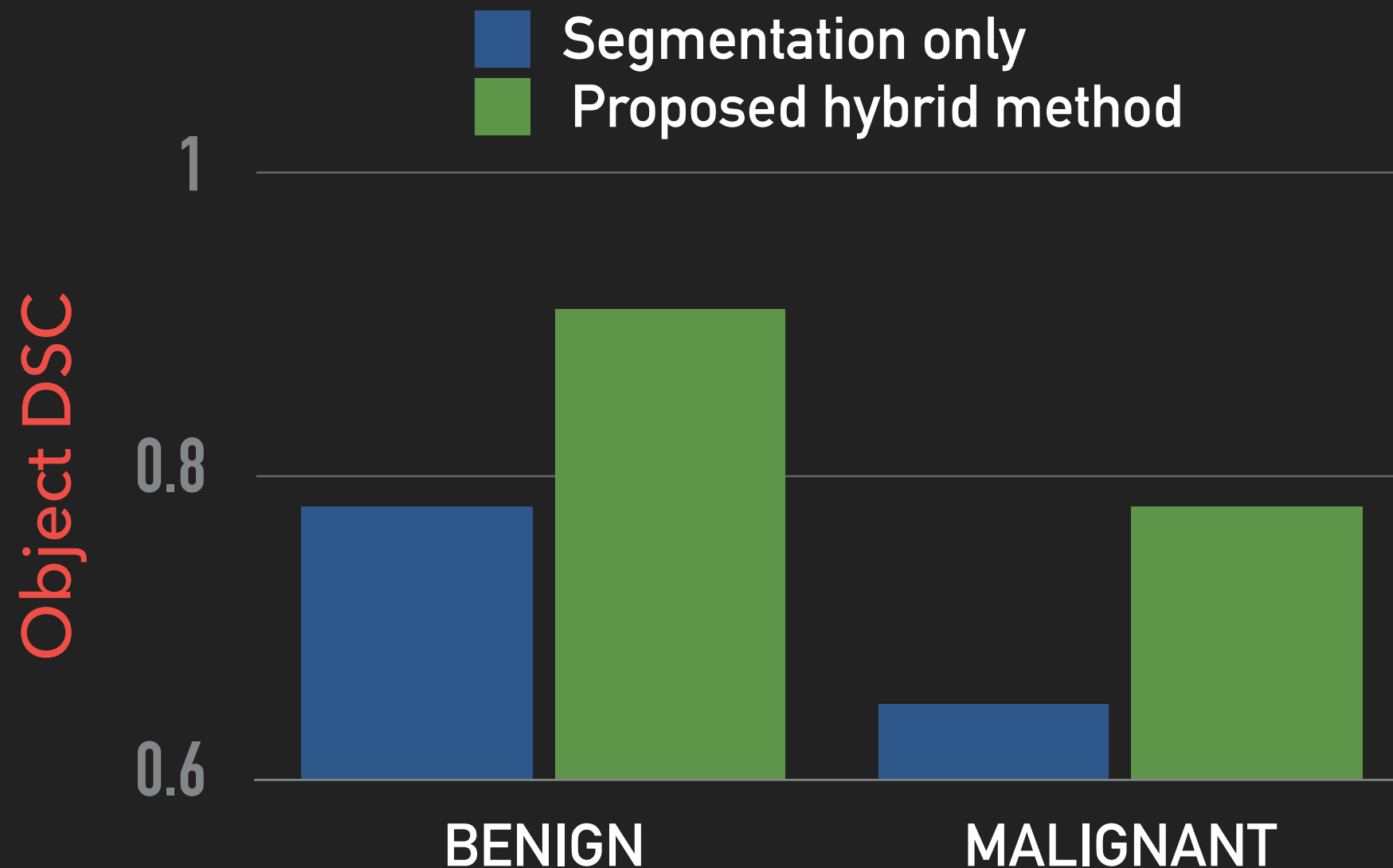


[3] Ronneberger et al. MICCAI (2015).

[4] Long et al. CVPR (2015).

SEGMENTATION RESULTS

For malignant glands, using our hybrid network (using VGG16) increased the segmentation Dice by **13%**.

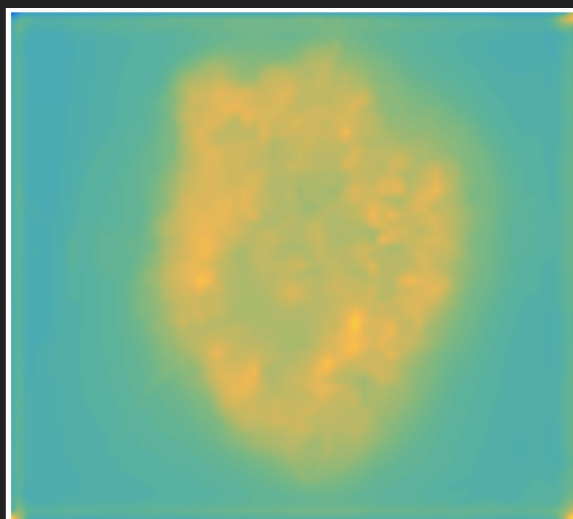


ISBI 2016 SKIN LESION SEGMENTATION CHALLENGE

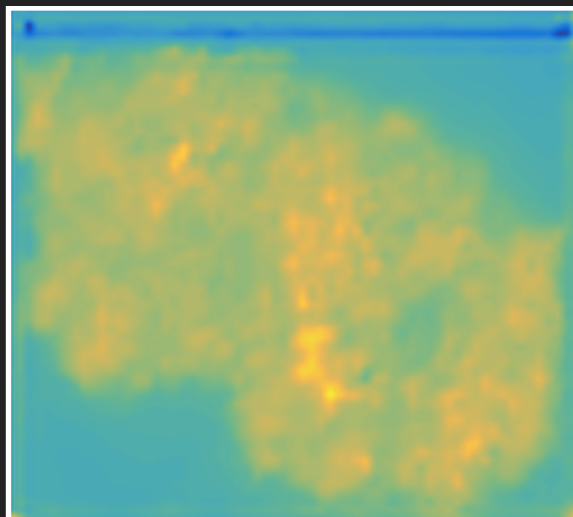
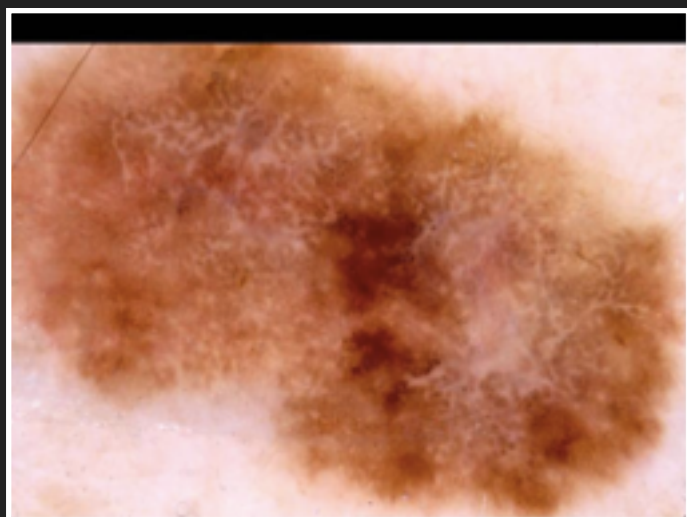
Input



Prediction



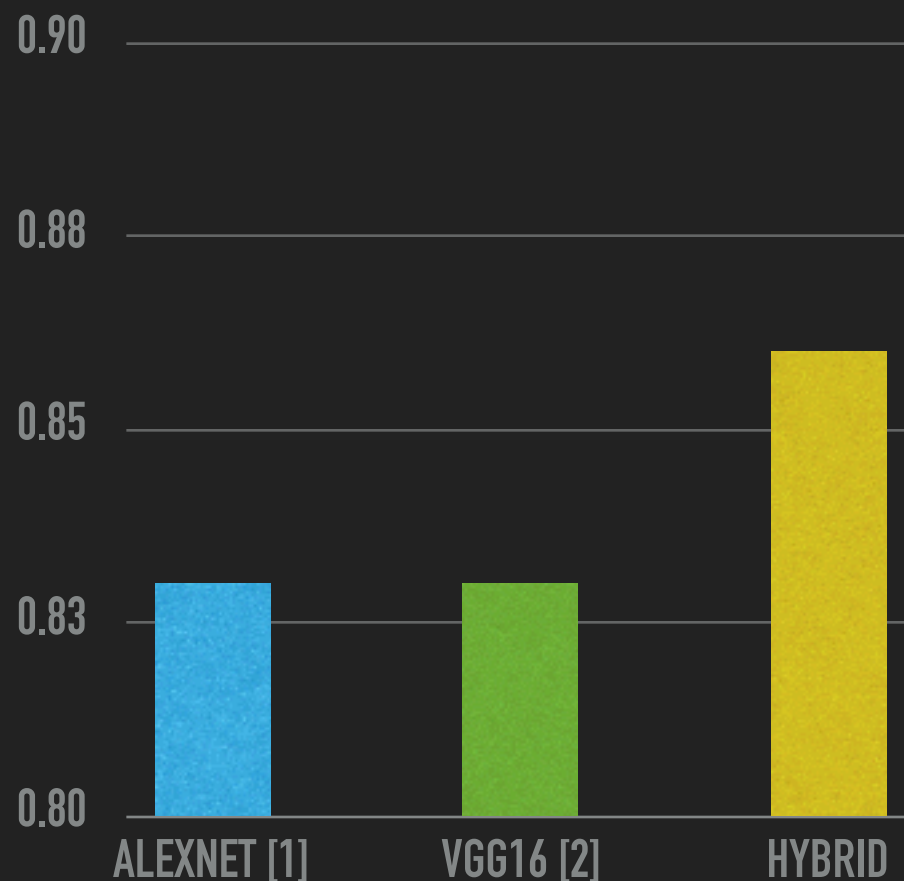
Output



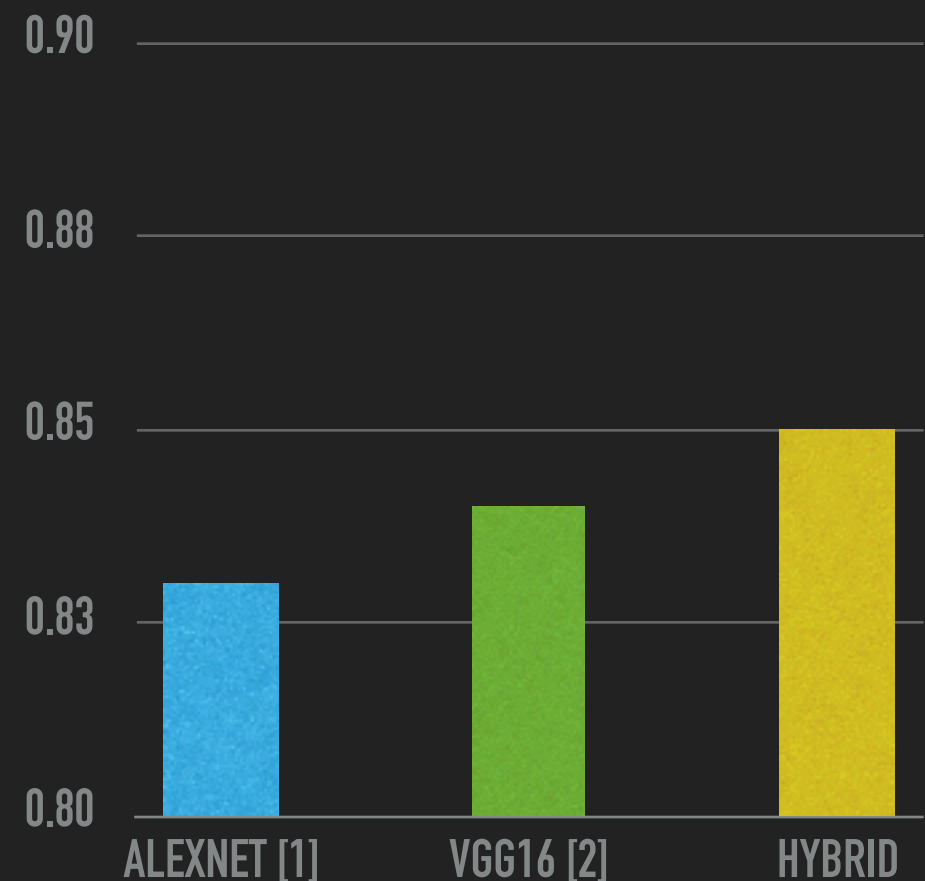
ISBI 2016 SKIN LESION SEGMENTATION CHALLENGE

Using segmentation priors increased the classification accuracy by **3%**.

Using class-specific priors increases the segmentation Jaccard by **2%**.



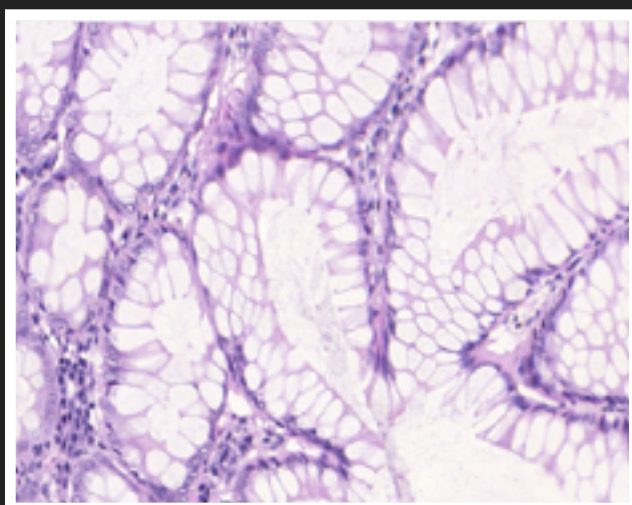
CLASS ACC



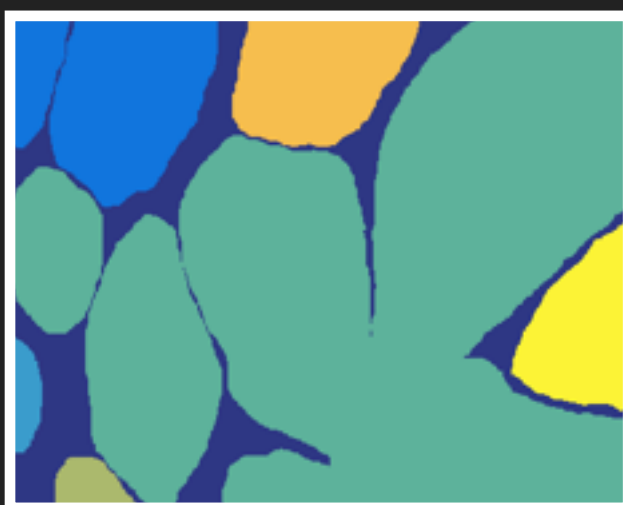
SEGM JACCARD

- ▶ We proposed a novel multi-loss network for **simultaneous** image segmentation and classification.
- ▶ We showed that:
 1. classification can facilitate the segmentation by introducing **class-specific spatial priors**.
 2. segmentation can benefit classification by providing **region-specific features**.

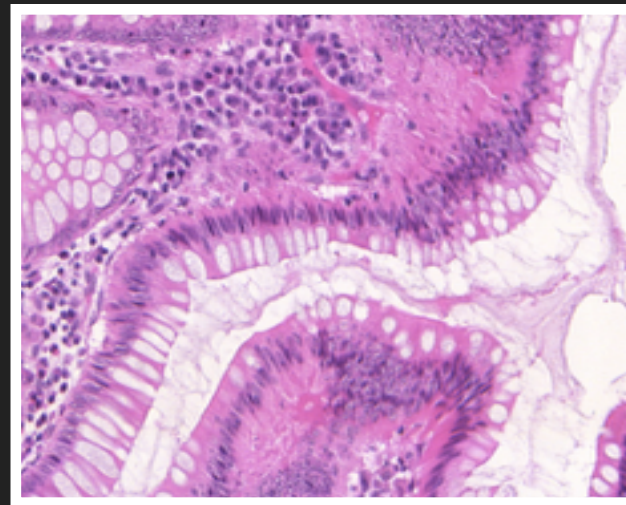
Benign Glands



Segmentation



Malignant Glands



Segmentation





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ENGAGING THE WORLD

THANK YOU.

contact: abentaie@sfu.ca