MULTICLASS WEIGHTED LOSS FOR INSTANCE SEGMENTATION OF CLUTTERED CELLS

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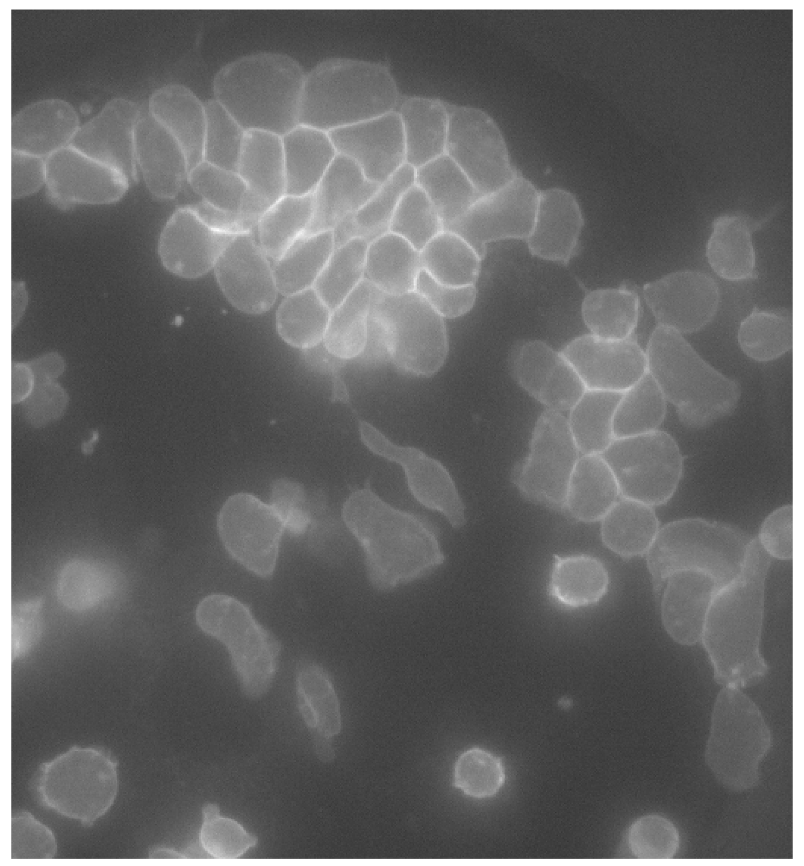
1. INTRODUCTION

- Difficulties when segmenting adjoining cells that can take any shape, when cluttered or isolated, and their touching borders have nonuniform patterns defeating classical segmentation approaches.

- The pixel count on adjoining borders is smaller than the total pixel count which contributes to numerical optimization difficulties.

Notation and definitions:

- Training set $S = \{(x_1, g_1), \ldots, (x_N, g_N)\}$
- Image $x_k\colon \Omega \to \mathbb{R}, \Omega \subset \mathbb{R}^2$
- Segmentation ground truth $g_k\colon \Omega \to \{0,1\}$
- Set of pixels in class l, $g^l = \{p \,|\, c(p) = l, p \in \Omega\}$
- Class assigned to pixel p, $c\colon \Omega \to \{0,\ldots,C\}$
- Indicator function over g^l, $y(p,l) = \begin{cases} 1 & \text{for } p \in g^l \\ 0 & \text{otherwise} \end{cases}$
- Our goal is to obtain a segmentation map $\hat{g} \approx g$
- FCN output probability map $z\colon \Omega \to \mathbb{R}^C$



2.1. CLASS AUGMENTATION

- Using a binary ground truth diminish the discriminative power of the network as the foreground and background intensity distributions overlap causing separation of pixels more difficult.

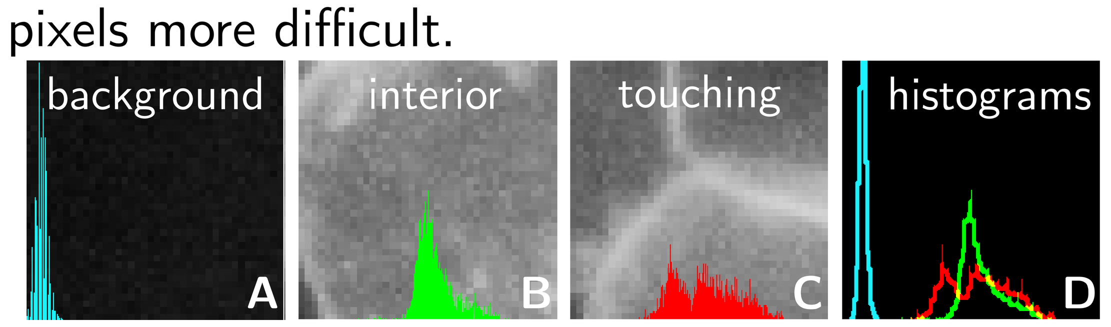


Fig 1: The distinct intensity and structural signatures of the three predominant regions – background (A), cell interior (B), in-between cells (C) – found in our images are shown above. Shown in panel (D) are the combined histogram curves for comparison.

- By considering a multiclass learning approach we enhance the discriminative resolution of the network and hence obtain a more accurate segmentation of individual cells.

Algorithm 1. Augment ground truth

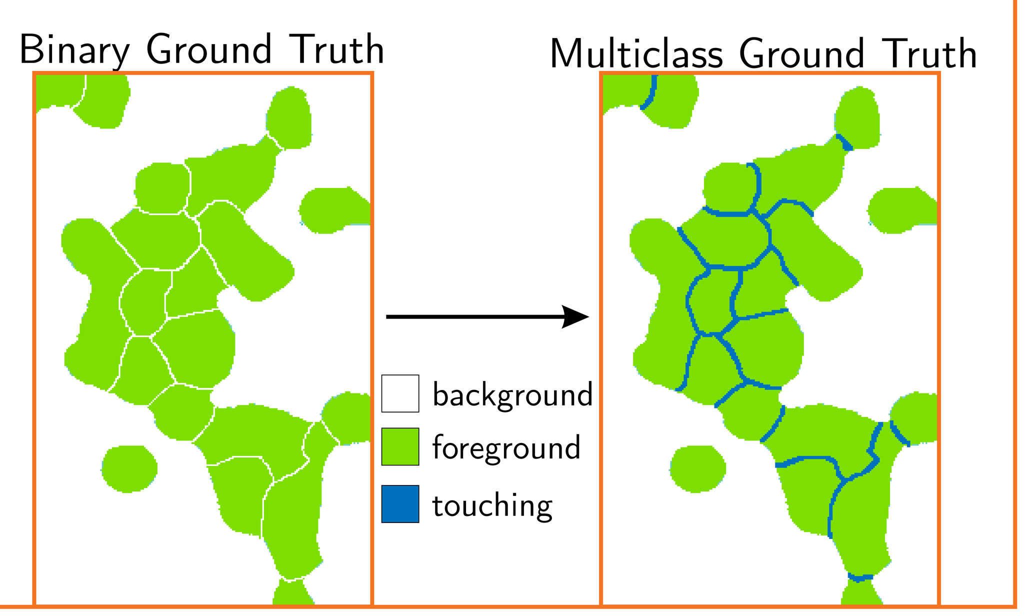
1: $g' \leftarrow (g \oplus s_e) \ominus s_e$

2: $g' \leftarrow g' - g$

3: $g' \leftarrow g' \oplus s_e$

4: $g \leftarrow g + (max(g) + 1) * g'$

$\oplus$Dilation $\ominus$Erosion



2.2 FOCUS WEIGHTS

The weighted cross entropy loss function is used to focus learning on important parts of an image:

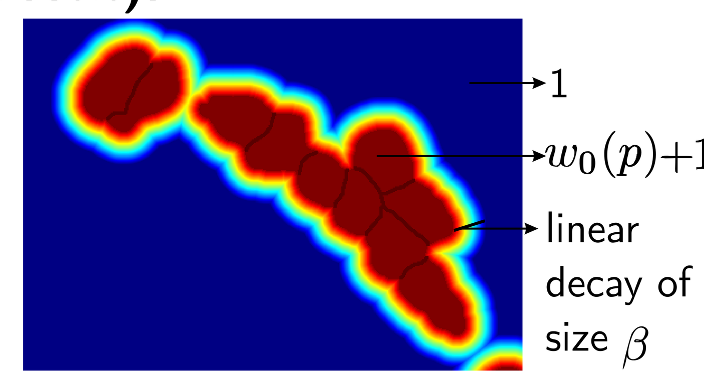
$$L(y,z) = -\sum_{p\in\Omega}\sum_{l=0}^{C} w(p,\theta) y(p,l) \log \text{smax}_l(z(p)) \quad \text{where } \text{smax}_l(u) = \frac{e^{u_l}}{\sum_{j=0}^{C} e^{u_j}}$$

usually employing the class balance weight map $w_0(p) = \frac{1}{|g^{c(p)}|}$

- **Distance transform based Weight Map (DWM):**

$$w^{DWM}(p,\beta) = w_0(p)\,(1 - \min(\phi_g(p)/\beta, 1)) + 1$$

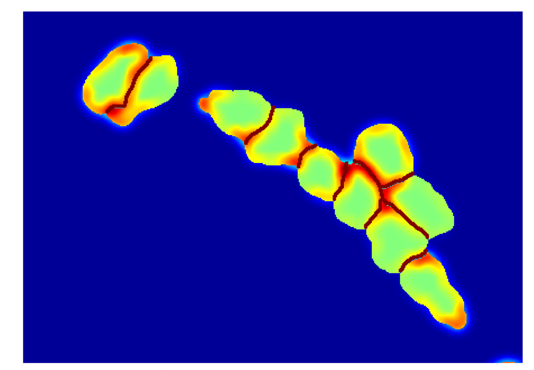
higher importance to background pixels near to contour



- **Shape Aware Weight Map (SAW):**

$$w^{SAW}(p,\tau,\sigma) = w_0(p) + F_\sigma * w_c(p,\tau) + 1$$

$$w_c(p,\tau) = \begin{cases} 1 - \phi_K(p)/\tau & \text{for } p \in \Gamma_H \\ 0 & \text{otherwise} \end{cases}$$



take into account small but important nuances around contours.

$\Gamma_H = \Gamma_l \cup \Gamma_r$ K:medial axis binary image

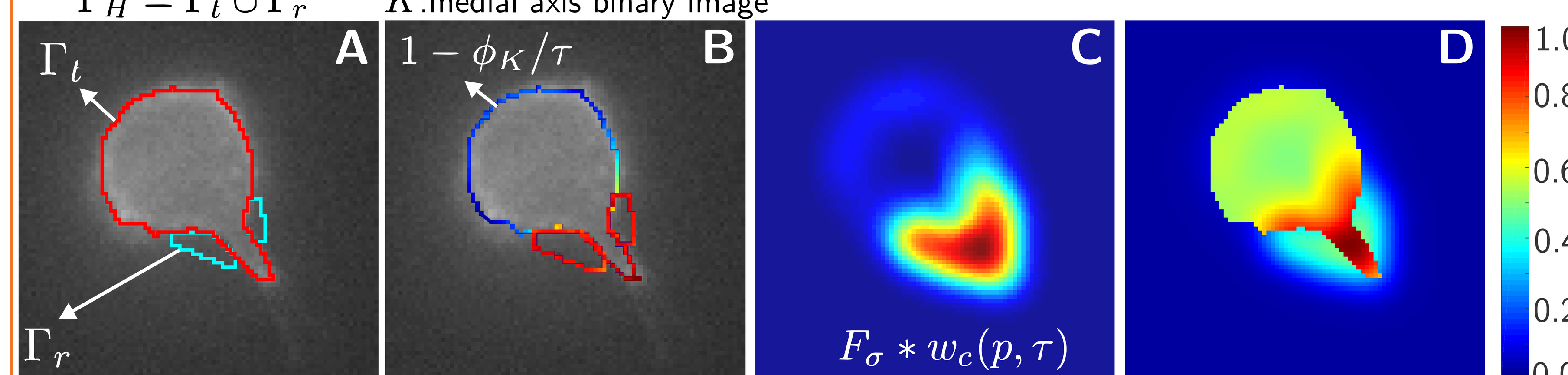
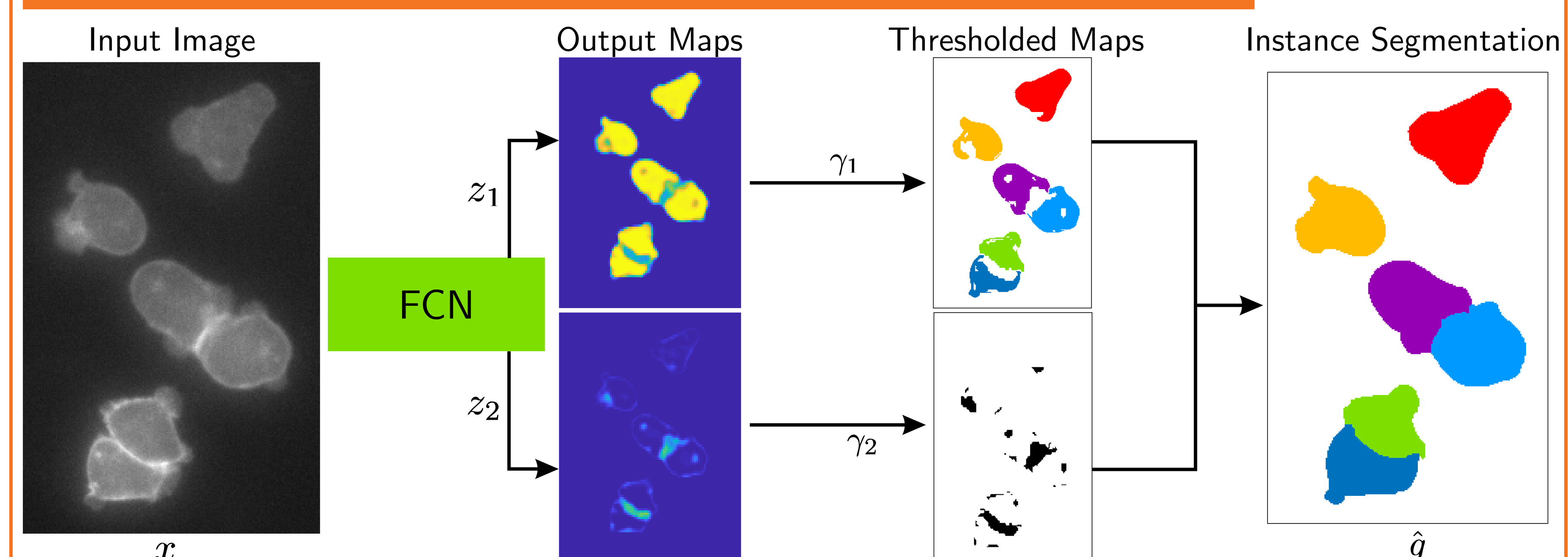


Fig 2: Contours of single cell Γ_l and concave complement Γ_r are shown in red and cyan in panel (A). Inverted distance transform to regions skeletons is show in panel (B). Copy padding and Gaussian smoothing propagates w_c values from Γ_H to neighboring pixels, panel (C). Final SAW weight map for the cell in (D). Color code is normalized to maximum value.

2.3 ASSIGNING TOUCHING PIXELS



3. RESULTS

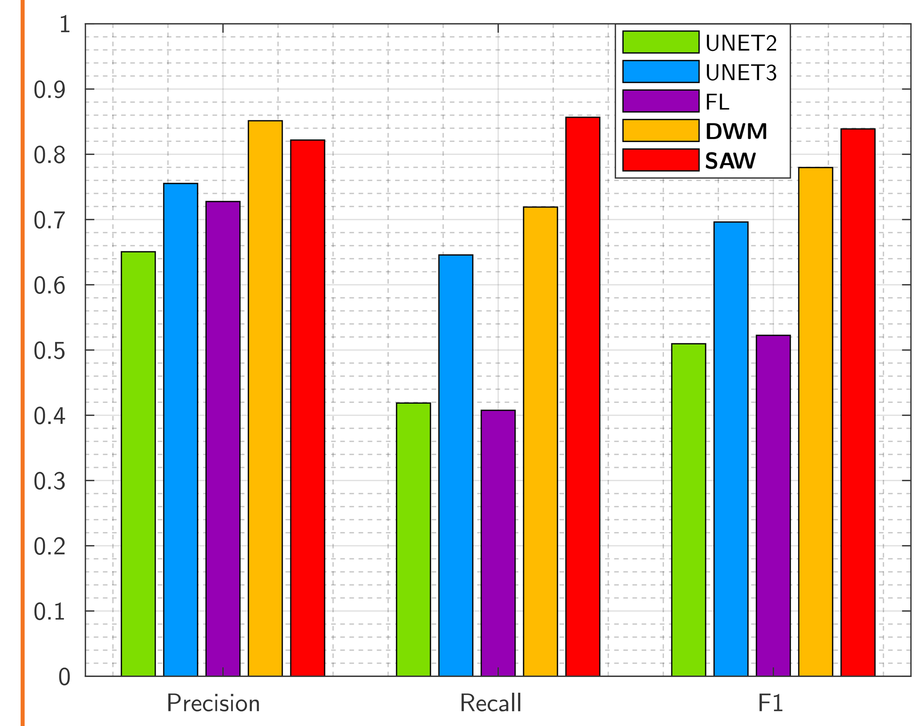


Fig 3: Instances detection performance. Precision, Recall and F1 for instances with Jaccard index above 0.5.

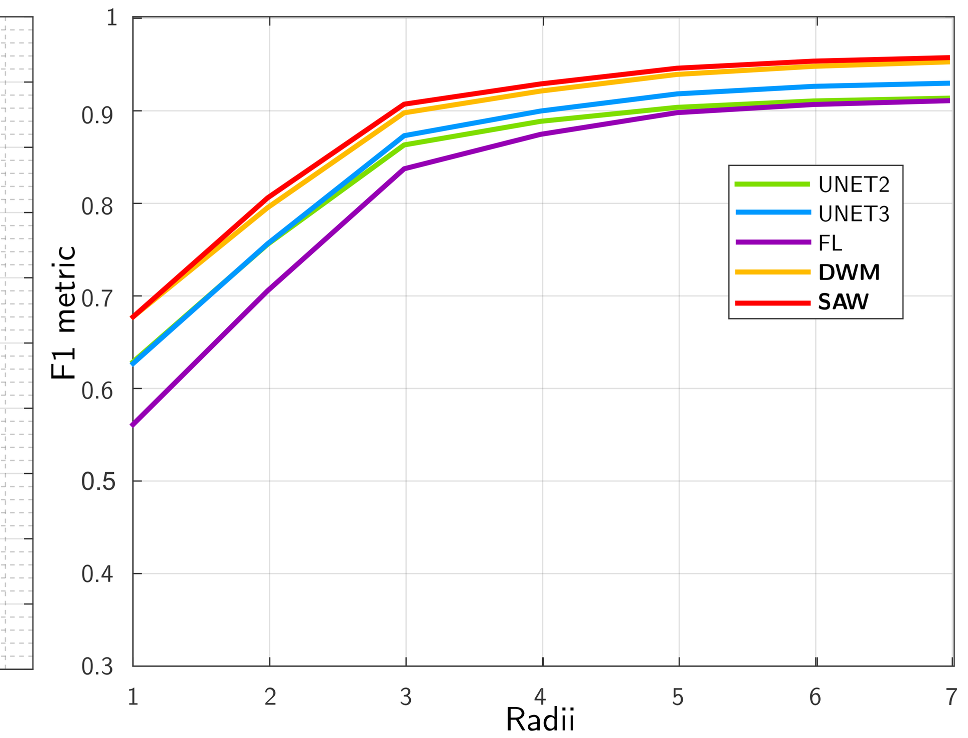


Fig 4: Segmentation contour adequacy. F1 scores for radii $\rho \in [1,7]$.

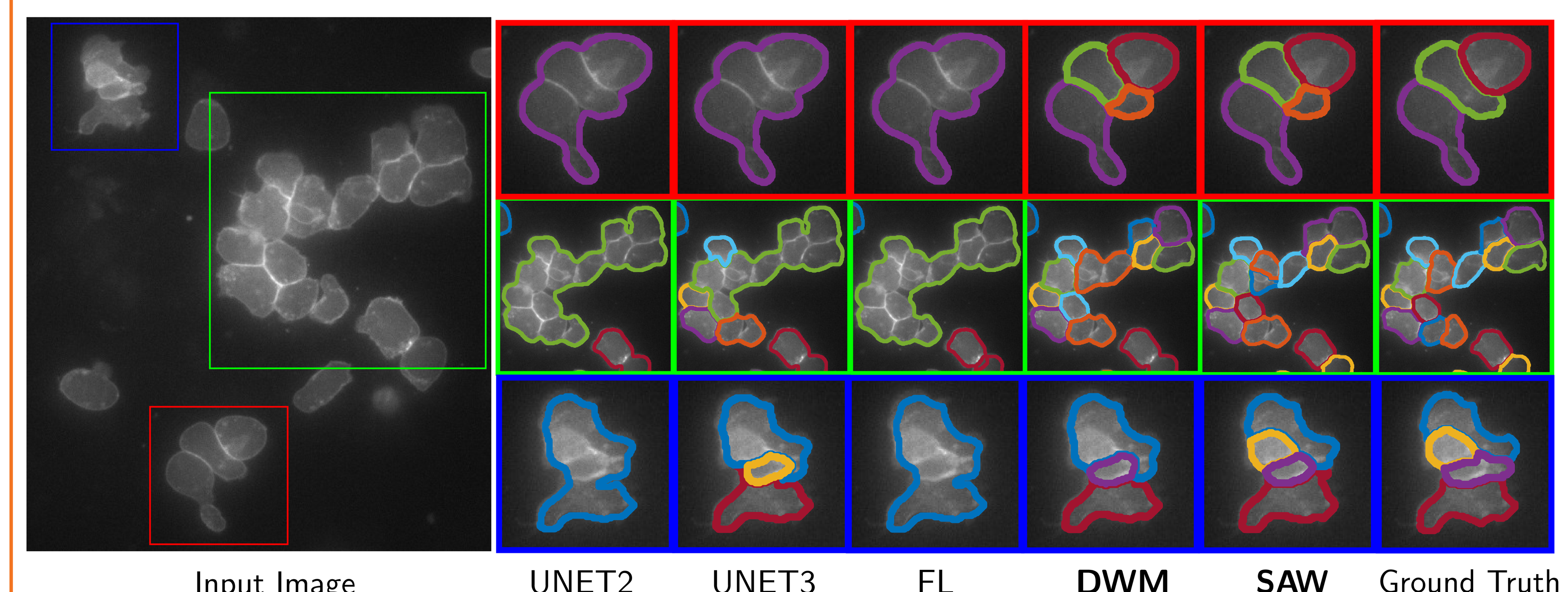


Fig 5: Example of instance segmentation obtained with UNET2, UNET3, FL, DWM and SAW and Ground Truth delineations. Contour colors are merely used to illustrate the separation of individually segmented regions.

4. CONCLUSIONS

- Learning with augmented labels for touching cells benefited instance segmentation.

- Shape based weight maps improved the effectiveness of the weighted cross entropy loss function in segmenting cluttered cells.

- Our experiments showed a significant performance improvement in instance segmentation of cluttered cells when SAW is used for training.

Implementation available at: https://github.com/fagp/dsegmentation