

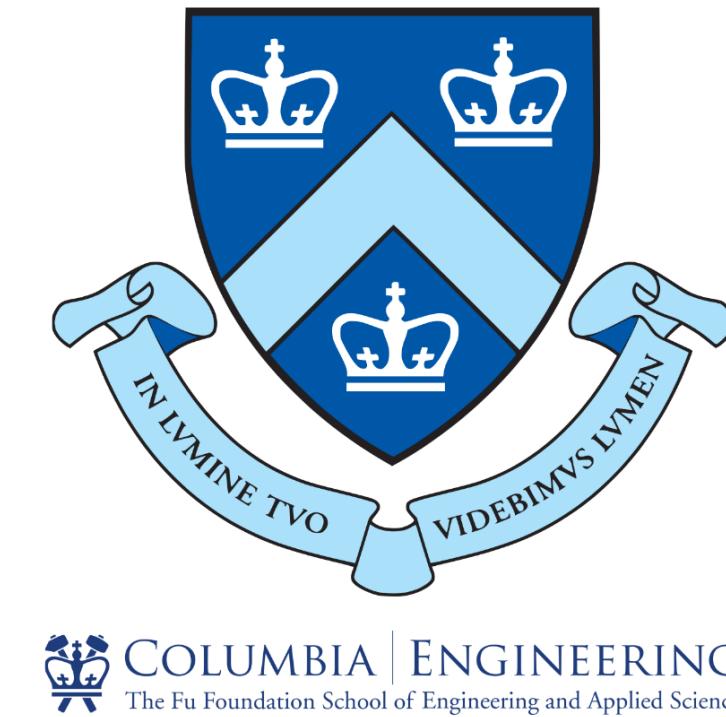
# TRANSFER LEARNING FRAMEWORK FOR CELL SEGMENTATION WITH INCORPORATION OF GEOMETRIC FEATURES

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## Abstract

- With recent advances in multiplexed imaging and spatial transcriptomic and proteomic technologies, cell segmentation is becoming a crucial step in biomedical image analysis.
- We propose a novel transfer learning, cell segmentation framework incorporating shape-aware and geometric features in a deep learning model, with multi-level watershed and morphological post-processing steps.
- Our results show that incorporation of geometric features improves generalizability to segmenting cells in *in situ* tissue images, using solely *in vitro* images [1] as training data.

## Model

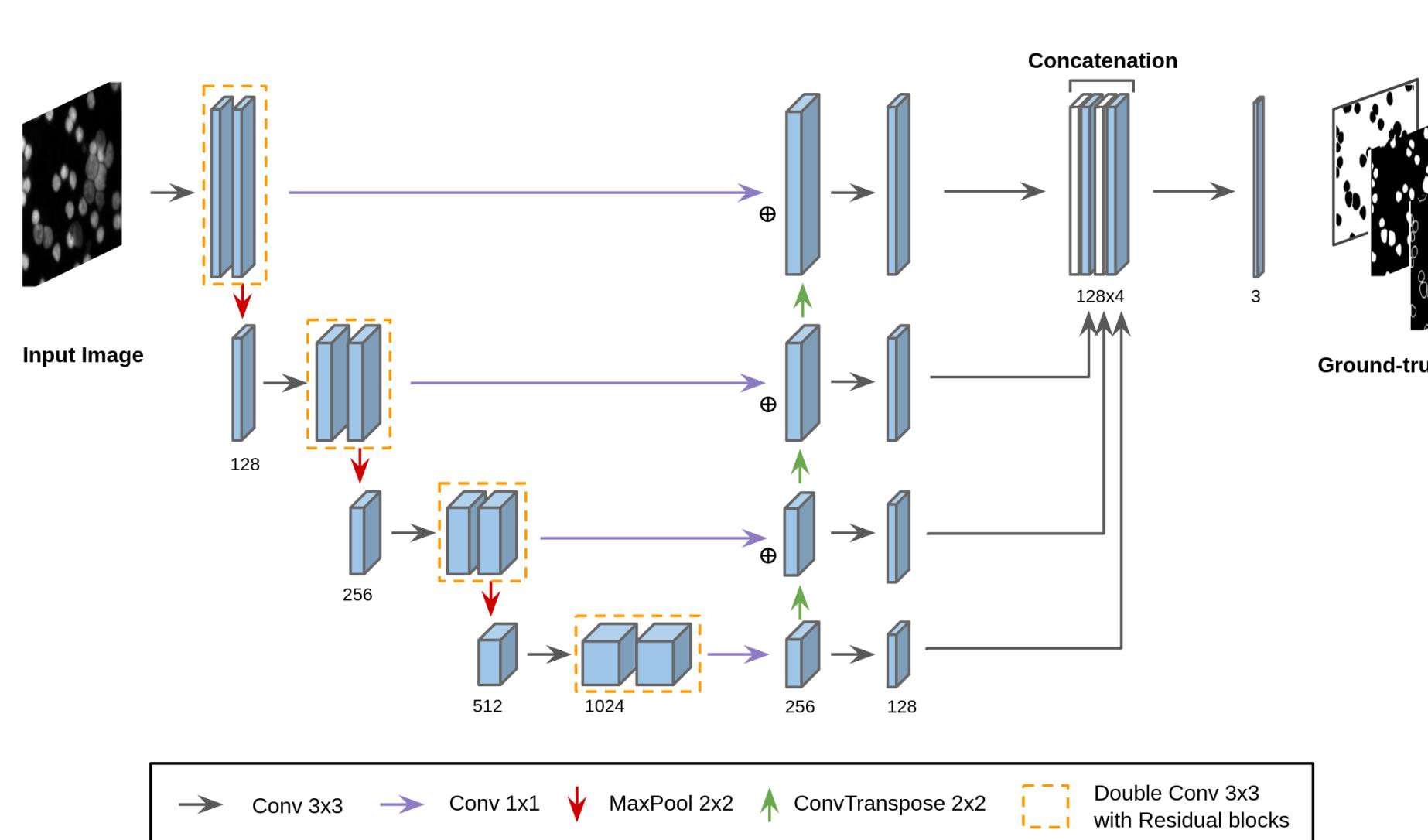


Fig. 1: Overview of the model architecture. We utilized a standard Feature Pyramid Networks (FPN) architecture with residual blocks, where feature maps from all resolution levels are directly connected to the output layer.

## Preprocessing & Shape-Aware Weight Maps

- We expanded upon the label augmentation for attaching cell borders [2] with:

- label 0: background pixels
- label 1: nuclei pixels
- label 2: attaching borders and cell contour pixels

- We applied the shape-aware weight maps (SAW) [2] to encode geometric properties of cells in the cross-entropy loss calculation during the training.

$$W_{\text{sa}}(p) = W_{\text{class}}(p) + \text{GaussianBlur}(W_{\text{complexity}}(p))$$

- We modified  $W_{\text{class}}(p)$  assignments to  $w_{p=i} = 1/\sqrt{|g_i|}$ ,  $g_i \in \{0, 1, 2\}$  to compensate for under-optimizing background regions with ultra low weights.

## Multi-level Watershed Post-processing

### Algorithm 1: Multi-level Watershed Post-processing

```

Input :  $G'$ : 3-channel prediction map
         $\theta$ : Cutoff value for selecting "convex-like" cells
Output :  $g_{ws}^T$ : Set of post-processed individual prediction masks
 $G_{\text{pred}} \leftarrow \{p \mid p \in G', g'_1(p) > 0.5\}$ 
 $G_{\text{region}} \leftarrow \{p \mid p \in G, g'_1(p) > 0.5 \text{ or } g'_2(p) > 0.5\}$ 
 $g^T \leftarrow \text{set of individual masks in } G_{\text{pred}}$ 
 $g_{\text{shape}}^T \leftarrow \emptyset$ 
 $a_{\text{avg}} \leftarrow \text{Mean}(\text{Area}(g)) \quad \forall g : \text{Solidity}(g) \geq \theta, g \in g^T$ 
 $d_{\text{avg}} \leftarrow \text{Mean}(2 \cdot \text{Area}(g)/\pi) \quad \forall g : \text{Solidity}(g) \geq \theta, g \in g^T$ 
for  $g \in g_{\text{pred}}^T$  do
    if  $\text{Solidity}(g) < \theta$  and  $\text{Area}(g) > a_{\text{avg}}$  then
         $t \leftarrow \text{InverseDistanceTransform}(g)$ 
         $m \leftarrow \text{LocalMaxima}(g, \text{minDistance} = d_{\text{avg}})$ 
         $g_{\text{shape}}^T \leftarrow \text{Watershed}(\text{image} = t, \text{markers} = m, \text{mask} = g)$ 
         $g_{\text{shape}}^T.append(g_{\text{shape}})$ 
    end
end
 $m^T \leftarrow \text{Centroid}(g_{\text{shape}}^T);$ 
 $t^T \leftarrow \text{InverseDistanceTransform}(g_{\text{shape}}^T);$ 
 $g_{ws}^T \leftarrow \text{Watershed}(\text{image} = t^T, \text{markers} = m^T, \text{mask} = g_{\text{shape}}^T);$ 

```

Model	Accuracy	F1	IoU	AUC	Hausdorff
U-Net	0.7494	0.7115	0.3091	0.6478	9.6090
U-Net + SAW	0.7543	0.7157	0.3168	0.6516	9.5787
FPN + SAW	0.7589	0.7244	0.3324	0.6606	9.4976
U-Net + Multi-level Watershed	0.8216	0.8114	0.5260	0.7624	8.6590
U-Net + SAW + Multi-level Watershed	0.8396	0.8338	0.5814	0.7934	8.4070
<b>FPN + SAW + Multi-level Watershed</b>	<b>0.8435*</b>	<b>0.8397*</b>	<b>0.6021*</b>	<b>0.8055*</b>	<b>8.2529*</b>

\* $p < 0.05$  (paired t-test comparing to U-Net)

Fig. 3: Performance comparison on MIBI *in vivo* dataset

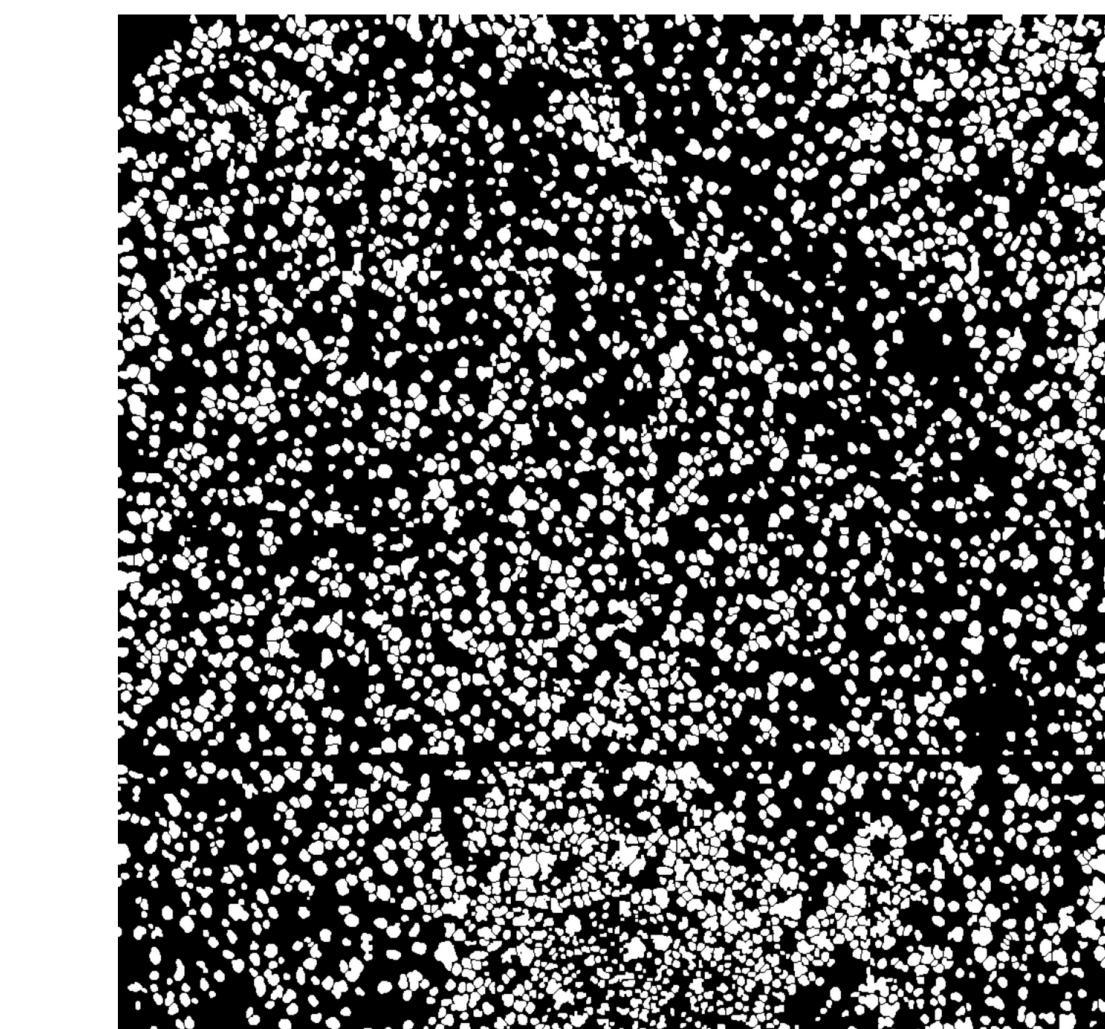


Fig. 4: Panoptic predictions (right) for patients compared to actual image (left) from MIBI-TOF dataset [3]

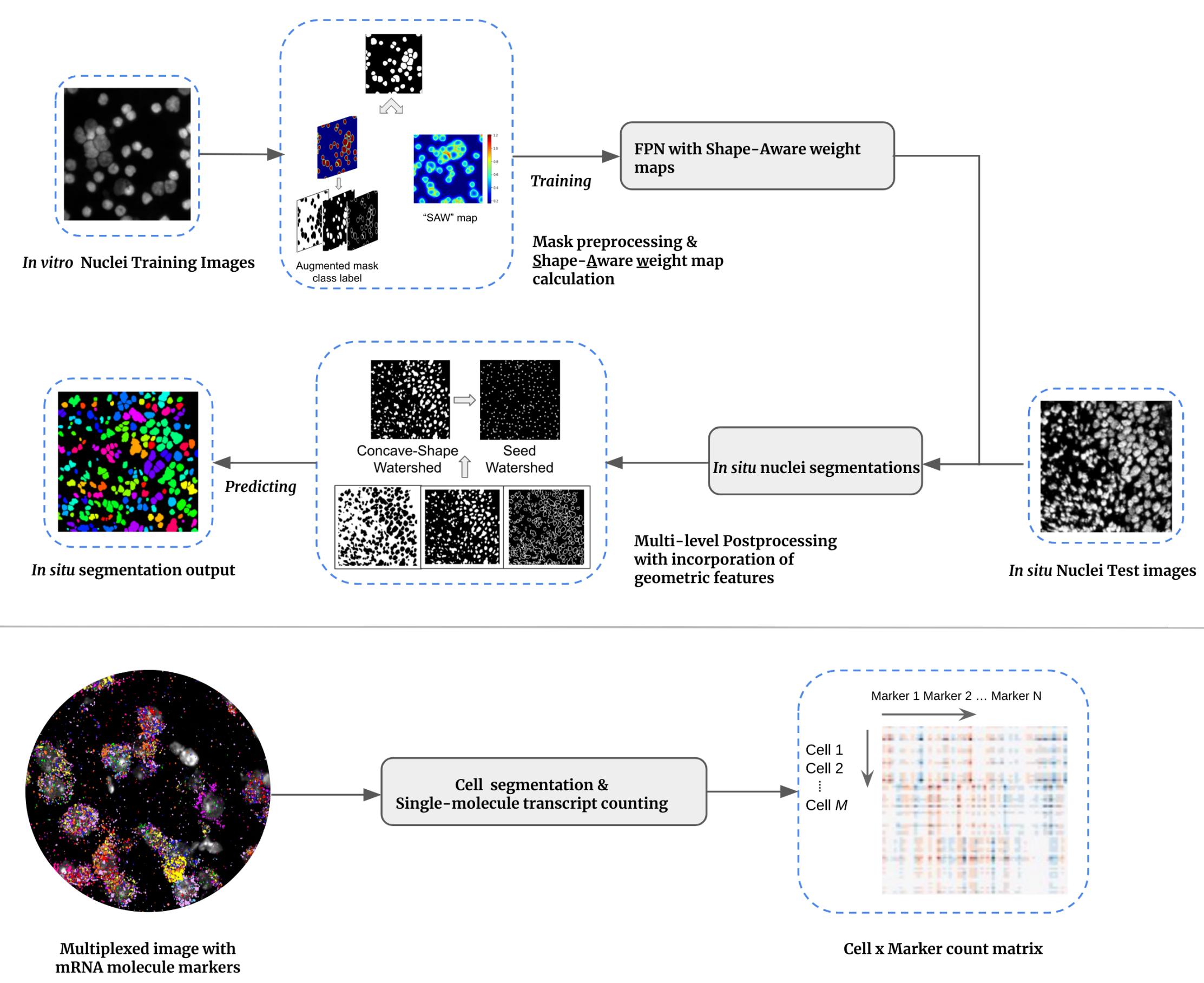


Fig. 2: Overview of transfer learning approach with shape-aware priors in a FPN and multi-level watershed post-processing.

## Results

## Conclusion

- Our cell segmentation pipeline leverages shape-aware map pre-processing and weights, and multi-level watershed post-processing to *in situ* tissue images captured with MIBI technology.
- Our future directions will aim at expanding this idea by incorporating topological priors [4] into the loss function in addition to the SAW geometric features, leveraging the concept of persistent homology.

## References

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