

## Conformal Prediction for Image Segmentation Using Morphological Prediction Sets



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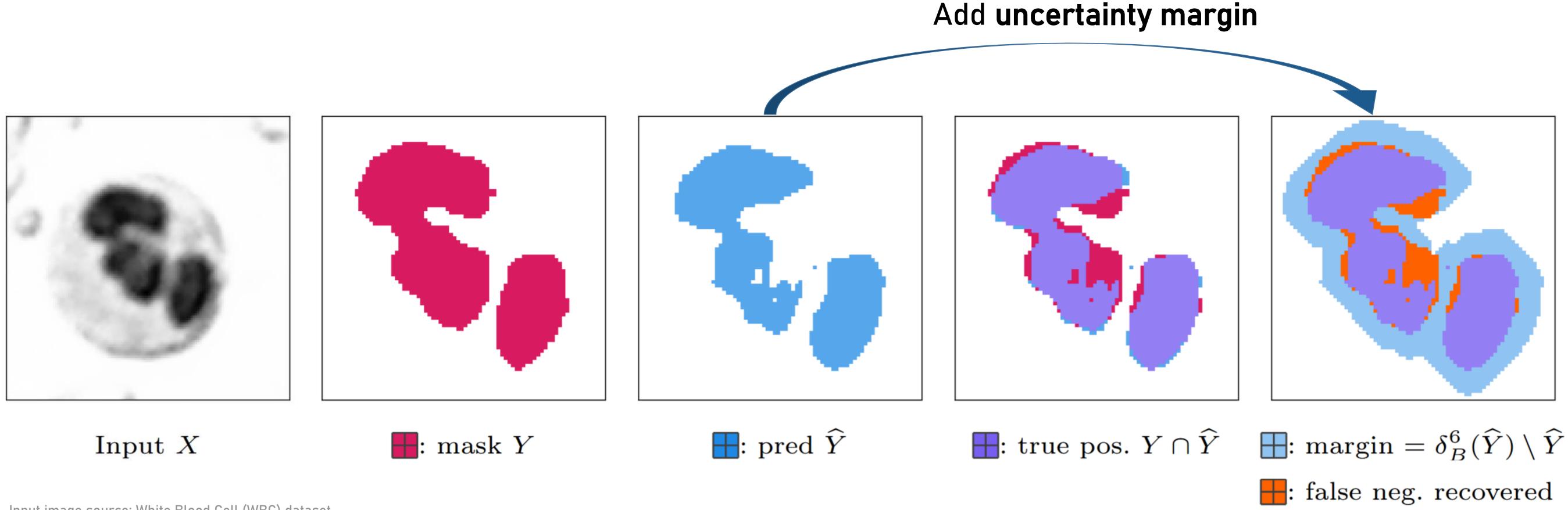


## **Conformal Prediction**

+ Mathematical Morphology

## Morphological Conformal Prediction

Model-agnostic - Distribution-free - Finite-sample



Input image source: White Blood Cell (WBC) dataset.
Zheng, X., et al. Fast and robust segmentation of white blood cell images by self-supervised learning. *Micron 107* (2018), 55–71.

Prediction Set: 
$$\mathcal{C}_{\lambda}(X) := \underbrace{(\delta_{B} \circ \delta_{B} \circ \cdots \circ \delta_{B})}_{\lambda \text{ dilations with kernel } B:} (\widehat{Y}) = \delta_{B}^{\lambda}(\widehat{Y})$$

$$B = \bigoplus$$
 (4-connectivity),

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 (8-connectivity), (...)

Acceptable error:  $\alpha \in (0,1)$  Tolerance hyperparam.:  $\tau \in (0,1)$ 

Calibration data:  $((X_i, Y_i))_{i=1}^n$ 

Nonconformity score:  $r(X_i,Y_i)=\inf\left\{\lambda\in\mathbb{N}\,:\, \frac{|Y_i\cap\mathcal{C}_\lambda(X_i)|}{|Y_i|}\geq \tau\right\}$ 

Estimation:  $\hat{\lambda} = \lceil (n+1)(1-\alpha) \rceil$ -th largest score in  $(r(X_i, Y_i))_{i=1}^n$ 

## Results = it works

Theorem: 
$$\mathbb{P}\left[\frac{|Y_{\text{test}} \cap \mathcal{C}_{\hat{\lambda}}(X_{\text{test}})|}{|Y_{\text{test}}|} \geq \tau\right] \geq 1 - \alpha$$

- ✓ Ensure statistically valid coverage
- ✓ Ensure fewer false negatives: margin captures false negatives
- $\checkmark$  Can use any extensive morphological operator (dilation, etc.)
- $\checkmark$  Margin size, smaller is better: can compare competing predictors, architectures, etc.



