

# Glomerulus Segmentation in Kidney Biopsies

## Computer Vision Project, Group 9

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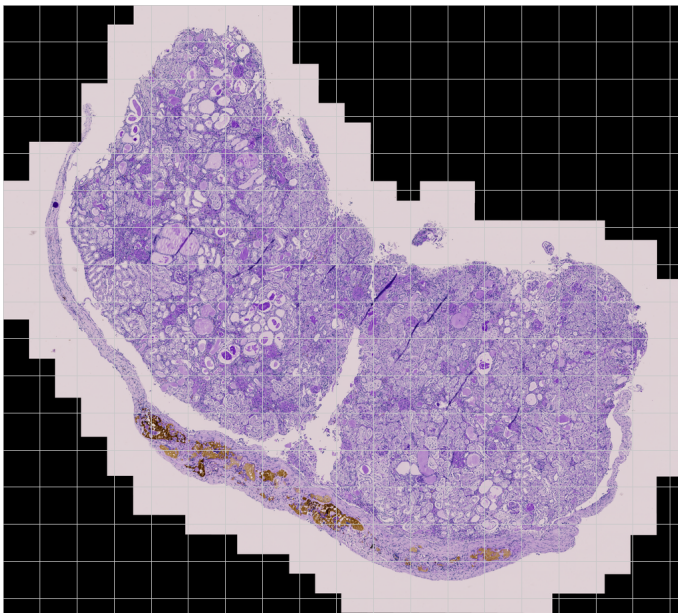
15.07.2025

# Problem Statement

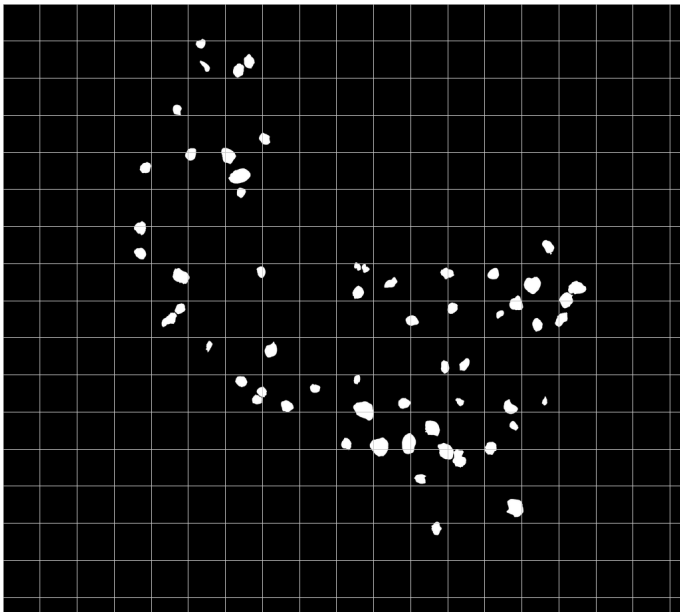
**General:** Accurate segmentation of glomeruli in kidney biopsy images is crucial for diagnosing chronic kidney diseases.

**Precise Tasks:** Segment glomeruli at patch-level and whole-slide level in kidney tissue images as part of the MICCAI 2024 KPIs Challenge.

# WSI Example: train\56Nx\12\_116



# WSI Mask Example: train\56Nx\12\_116



- Standard UNet architecture with double convolution layers and skip connections.
- Dilated bottleneck for multi-scale feature extraction.<sup>1</sup>
- Channel counts scale with variable patch size.
- Combined BCE and Dice loss (BCEDiceLoss) to address class imbalance. Focusing on recall and  $F_1$ -score.

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<sup>1</sup>Li et al. (2021)

- Trained on official KPIs dataset (train/val/test splits).
- Hyperparameter tuning: BCE/Dice ratio, dice smooth, positive class weighting for BCE, base learning rate of Adam optimizer.
- Experiments with different patch sizes (256, 2048 px) and data subsets.
- Evaluated using accuracy, precision, recall, and  $F_1$ -score.
- Qualitative assessment via visual inspection.

# Metrics of our best performing models

Patch size	Split	Accuracy	Precision	Recall	$F_1$ -score
256	Validation	0.9781	0.7479	0.7660	0.7569
	Test	0.9757	0.7537	0.7133	0.7330
2048	Validation	0.9705	0.9299	0.3662	0.5255
	Test	0.9643	0.9159	0.2616	0.4070

## Hyperparameters:

- BCEDiceLoss Ratio = 0.8
- BCE Positive Weight = 25
- Dice Smooth =  $10^{-6}$
- Learning Rate =  $10^{-4}$

## **Implemented patching pipeline with the following hyperparameters:**

- Patch size
- Patch overlap (stride)
- Trivial patch threshold for positive pixels

## **Possible next steps:**

- Implementation of a stitching pipeline to combine patch predictions into a full WSI mask.
- Train VariableUNet with complete patching and stitching pipeline.



## What worked:

- BCE + Dice loss crucial for recall and  $F_1$ -score.
- Hyperparameter tuning improved glom detection.
- WSIs can be patched for patch-level segmentation.

## Limitations:

- Instability in training, especially with full-size patches.
- Our configurations, trained on small patches, did not generalize well to larger patches.
- No empirical validation on WSI segmentation due to time constraints.

## In Retrospect:

- Greater emphasis on pre- and post-processing (downsampling patches and upsampling predictions).
- More in-depth data exploration regarding samples of different diseases.

## Future Work:

- Exploring different model architectures and methods.
- Search for more robust hyperparameters and domain adaptation.
- Exploring different WSI patching thresholds.

# Appendix

# UNetArchitecture

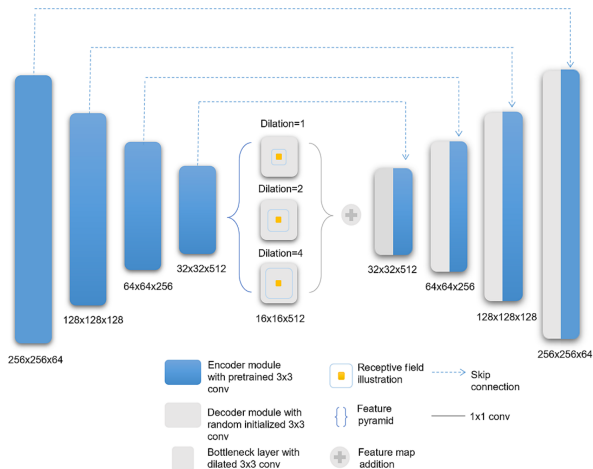
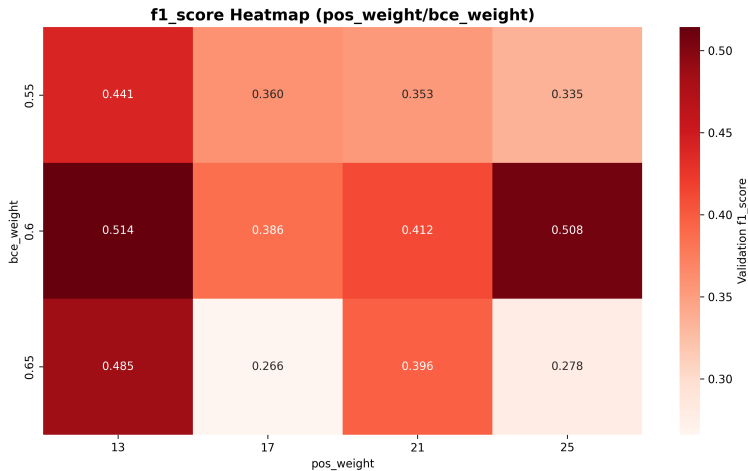


Figure: Doi: 10.1117/1.JMI.8.6.067501

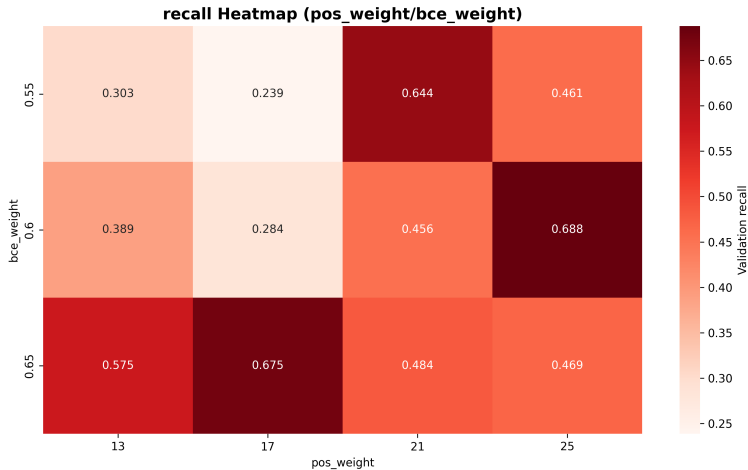
# Double Convolution

```
1 class DoubleConv(nn.Module):
2     def __init__(self, in_channels, out_channels):
3         super().__init__()
4         self.double_conv = nn.Sequential(
5             nn.Conv2d(in_channels, out_channels, 3,
6                       padding=1),
7             nn.BatchNorm2d(out_channels),
8             nn.ReLU(inplace=True),
9             nn.Conv2d(out_channels, out_channels, 3,
10                      padding=1),
11             nn.BatchNorm2d(out_channels),
12             nn.ReLU(inplace=True),
13         )
14
15     def forward(self, x):
16         return self.double_conv(x)
```

# Heat Map F1 Score



# Heat Map Recall



# FlipFlop Graph

