Glomerulus Segmentation in Kidney Biopsies

Computer Vision Project, Group 9

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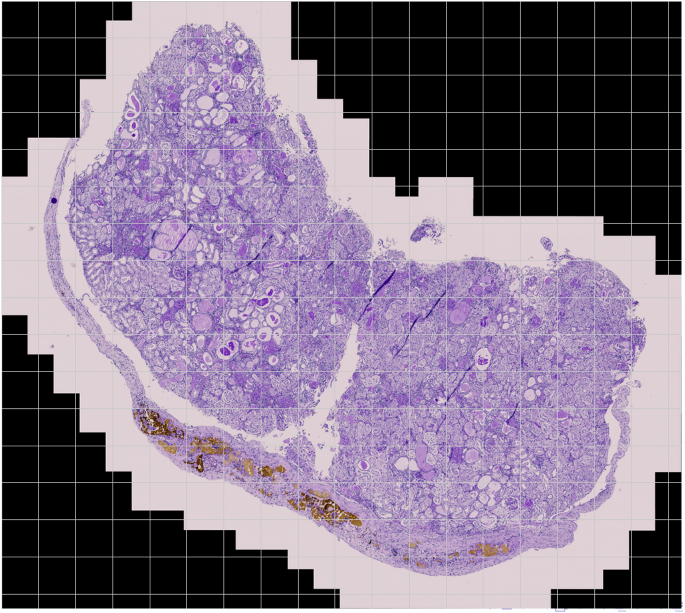
Problem Statement

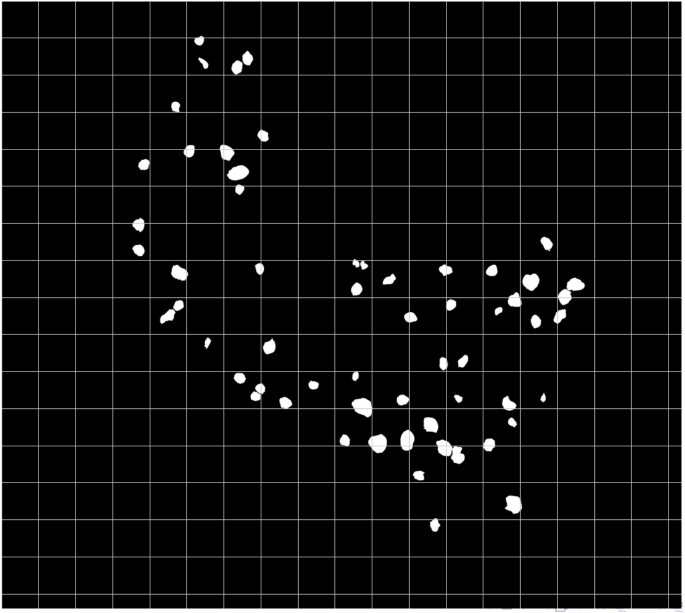
General: Accurate segmentation of glomeruli in kidney biopsy images is crucial for diagnosing chronic kidney diseases.

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



VariableUNet Model

- Standard UNet architecture with double convolution layers and skip connections.
- Dilated convolutions in the bottleneck (with dilation rates 1, 2, 4 on $\frac{1}{3}$ of the channels each) for multi-scale feature extraction.[1]
- Channel quantities scale with variable patch size.

[1] Li et al. (2021)

Experimental Design

- Trained on official KPIs dataset (train/val/test splits).
- Combined binary cross entropy (BCE) and Dice loss to address class imbalance.
- Hyperparameter tuning: BCE/Dice ratio, Dice smooth, positive class weighting for BCE, learning rate for Adam optimizer.
- Experiments with different patch sizes (256^2 and 2048^2 pixels) 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 $= 10^{-4}$

WSI Segmentation

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 using the complete patching and stitching pipeline.

Discussion

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.

Discussion

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.
- Continued work on WSI segmentation pipeline.

Backup

UNet Architecture

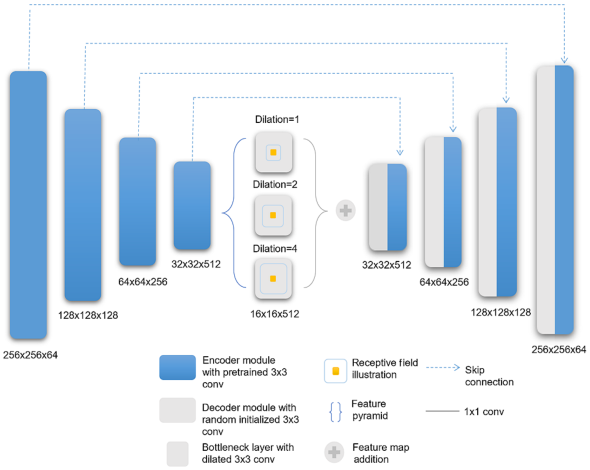


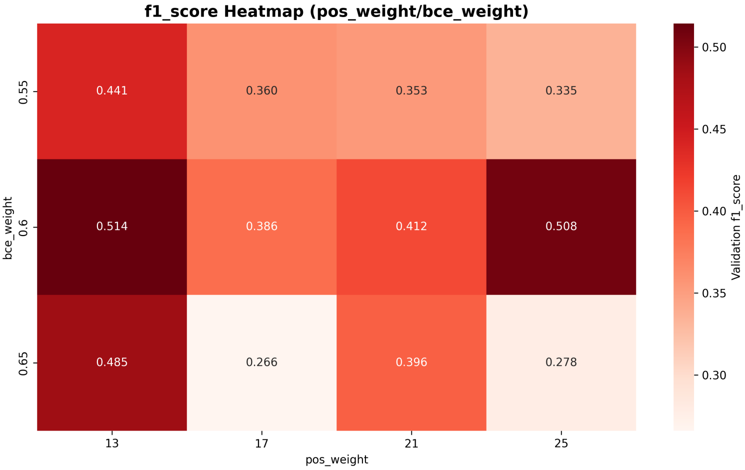
Figure: Source: Li et al. (2021), Figure 3 (edited)

Double Convolution in our Code Base

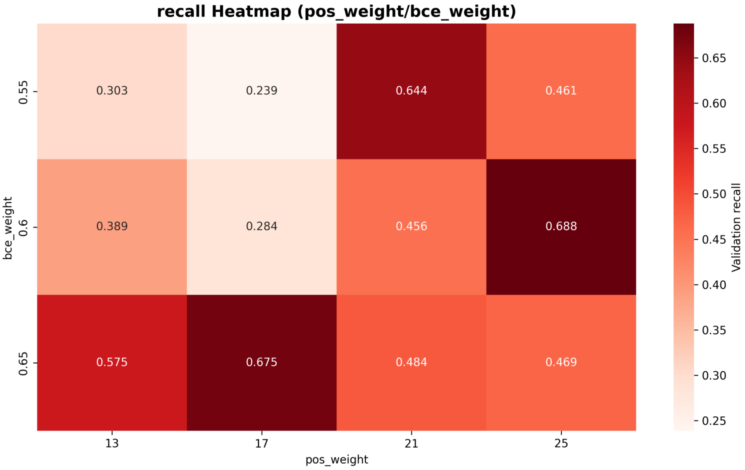
```python
class DoubleConv(nn.Module):
    def __init__(self, in_channels, out_channels):
        super().__init__()
        self.double_conv = nn.Sequential(
            nn.Conv2d(in_channels, out_channels, 3,
                padding=1),
            nn.BatchNorm2d(out_channels),
            nn.ReLU(inplace=True),
            nn.Conv2d(out_channels, out_channels, 3,
                padding=1),
            nn.BatchNorm2d(out_channels),
            nn.ReLU(inplace=True),
        )

    def forward(self, x):
        return self.double_conv(x)
```

F_1-Score Heat Map from Experiment 2



Recall Heat Map from Experiment 2



FlipFlop Graph from Experiment 3