



A lightweight model for CT segmentation of maxillary sinuses in children with chronic rhinosinusitis



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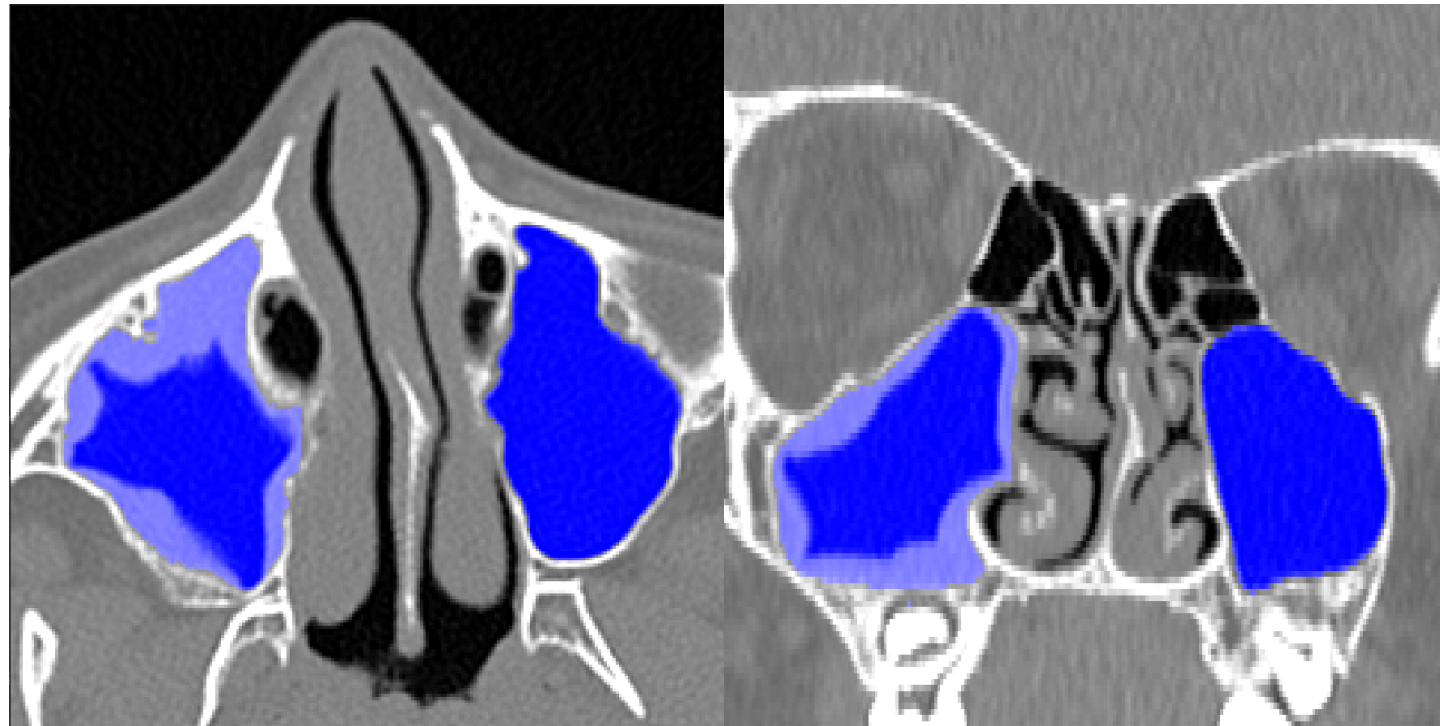
Chronic rhinosinusitis in children



- In chronic rhinosinusitis sinuses are partially filled with mucus
- The goal is to compute the total volume of each maxillary sinus and its fraction filled with mucus
- Pediatric cases are more difficult but very important



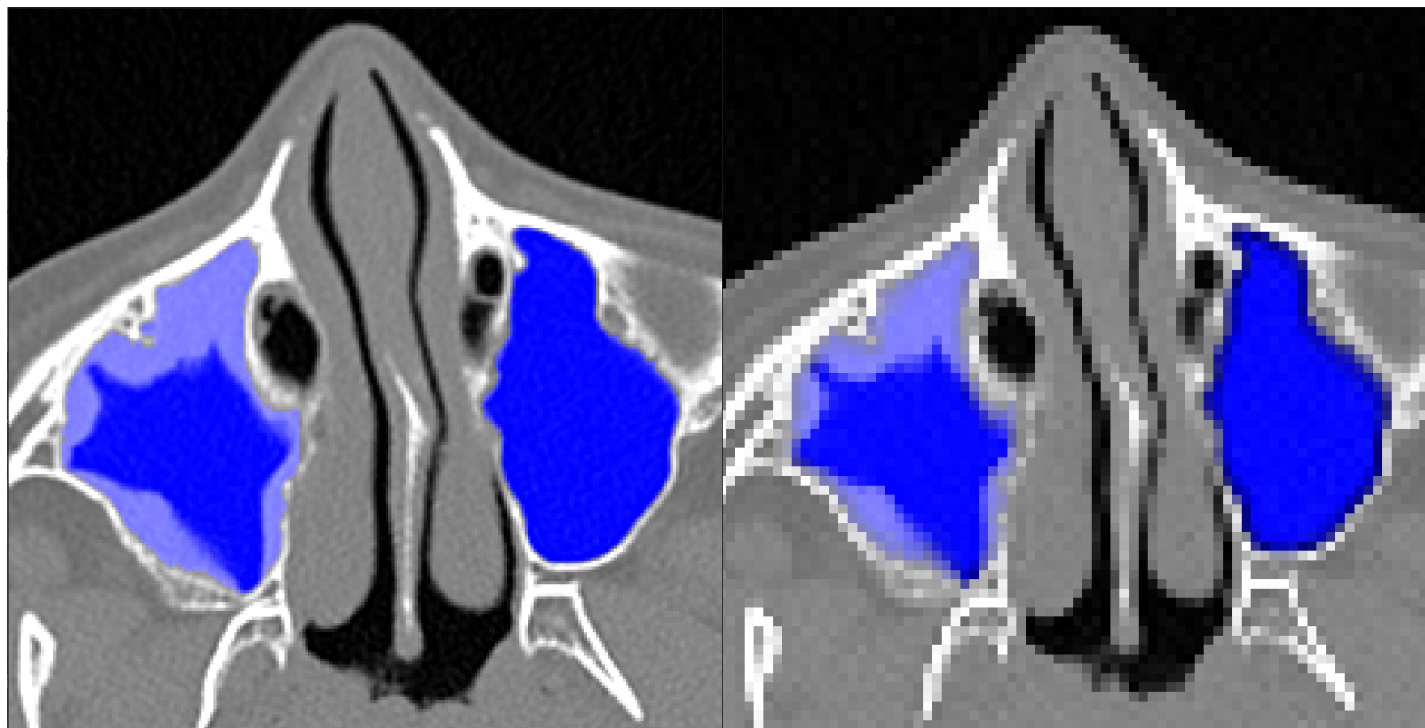
Segmentation task



- A neural network segments maxillary sinuses as one class
- Left and right are distinguished by diagonalizing the inertia tensor
- Free and congested regions are identified based on HU values
- Five human experts segmented 92 scans using 3D Slicer



Fractional labels in reduced resolution



- CT images are about $512 \times 512 \times 448$ with $0.3 \times 0.3 \times 0.6 \text{ mm}^3$ voxels
- They are scaled down to $192 \times 192 \times 168$ with $1 \times 1 \times 1 \text{ mm}^3$ voxels
- Fractional labels account for the partial-volume effect



Receptive field



Conv(1, 1, 3, 1)

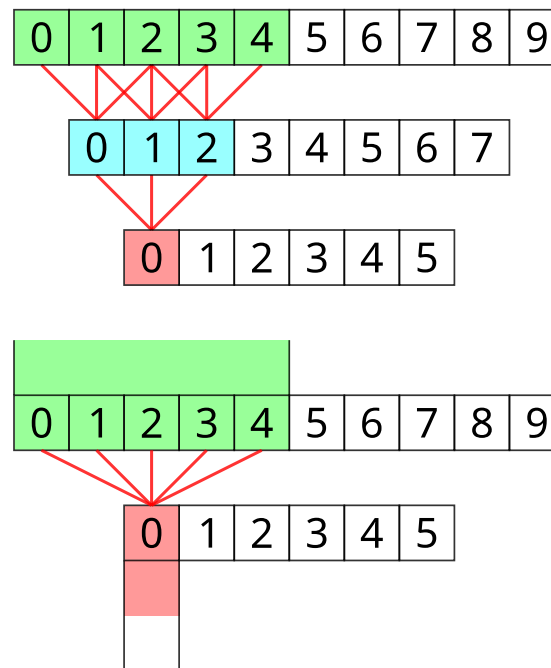
Conv(1, 1, 3, 1)

Receptive field of 5

Stride of 1

Output patch of 1

Output field of 1



- Receptive field is a set of input voxels seen by one output voxel
- Large architectures often have different receptive fields for different output voxels
- We aim at equal receptive field for each output voxel



Output patch and field



Conv(1, 1, 4, 2)

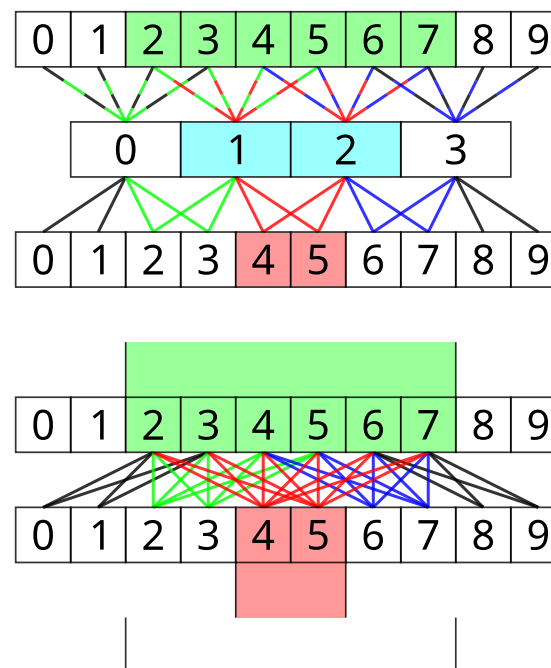
ConvTranspose(1, 1, 4, 2)

Receptive field of 6

Stride of 2

Output patch of 2

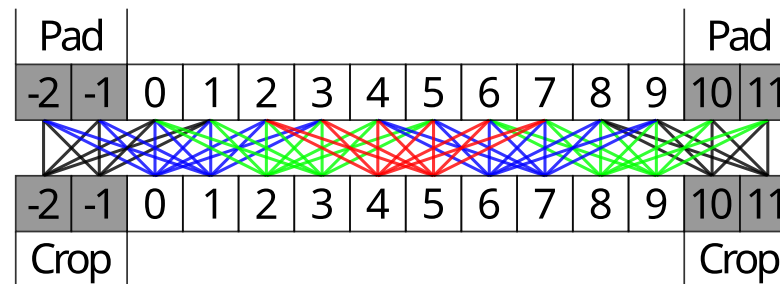
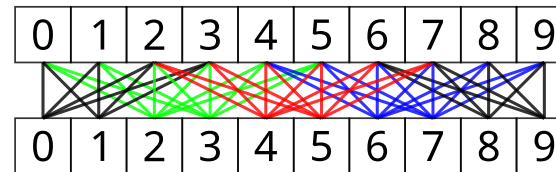
Output field of 6



- Output patch is a set of output voxels that depend on the same receptive field and only on that field
- Output field is what the model outputs when fed with a single receptive field



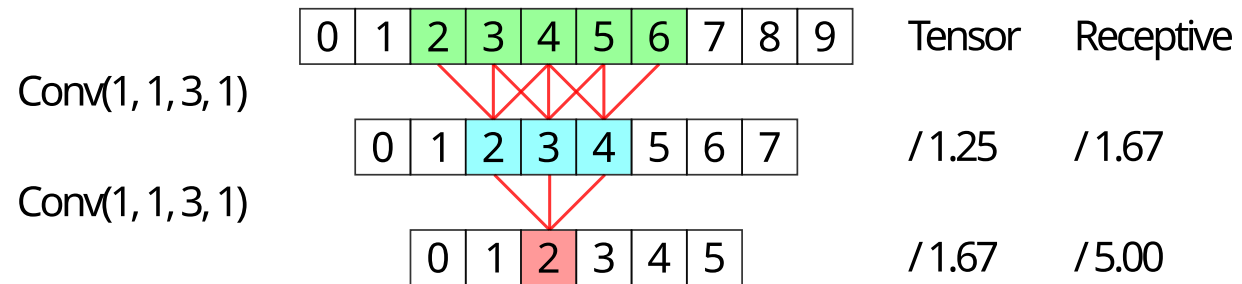
Padding and cropping



- Large architectures use zero-padding in every convolutional layer to maintain spatial dimensions, which inserts meaningless zeros
- Our model applies zero-padding only in the input layer where it is equivalent to the image background



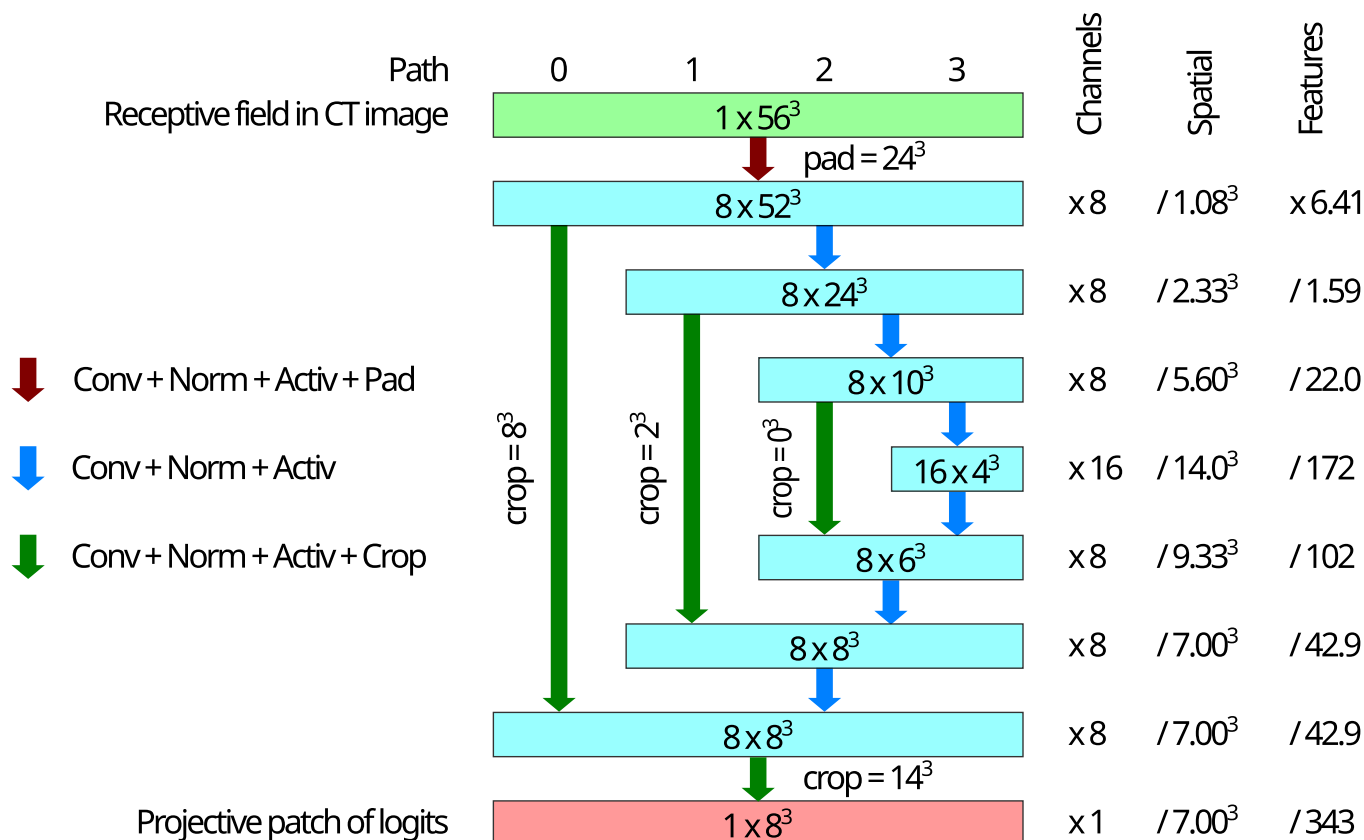
Receptive features



- Adjusting the number of channels involves counting relevant features in each layer
- People often consider just the tensor shapes
- We count receptive features affecting a single output patch
- We adjust the channel count to first inflate and then shrink the set of receptive features



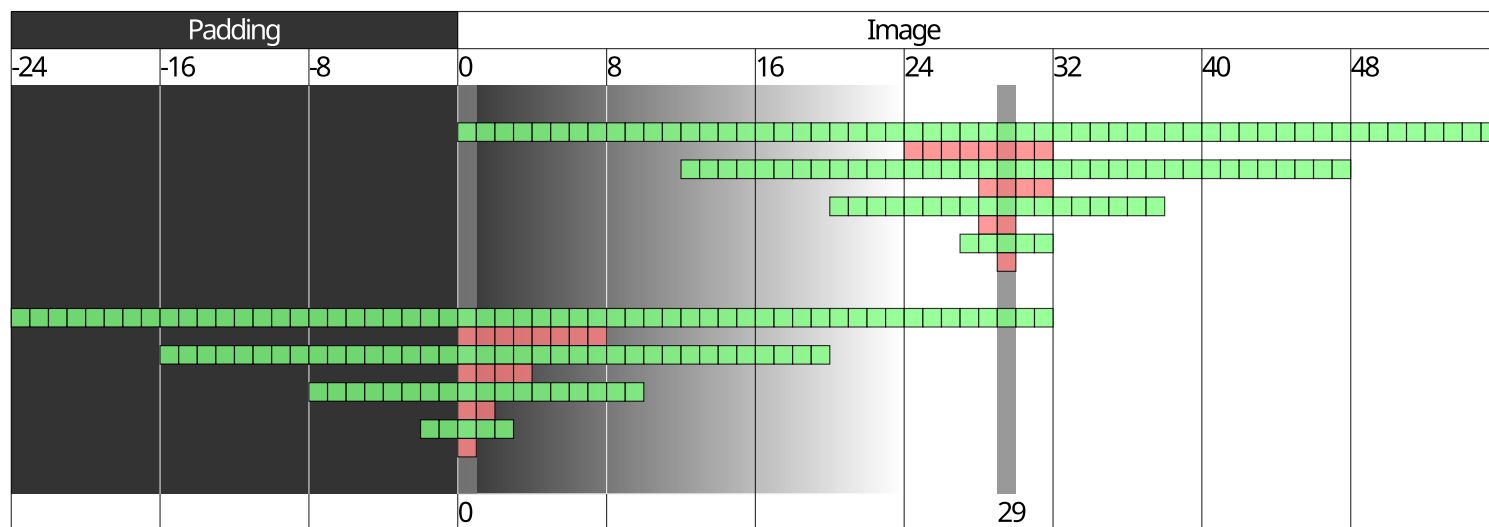
Architecture



- 16 convolutional layers comprising 39,745 parameters
- 4 receptive fields and output patches corresponding to the 4 paths



Paths

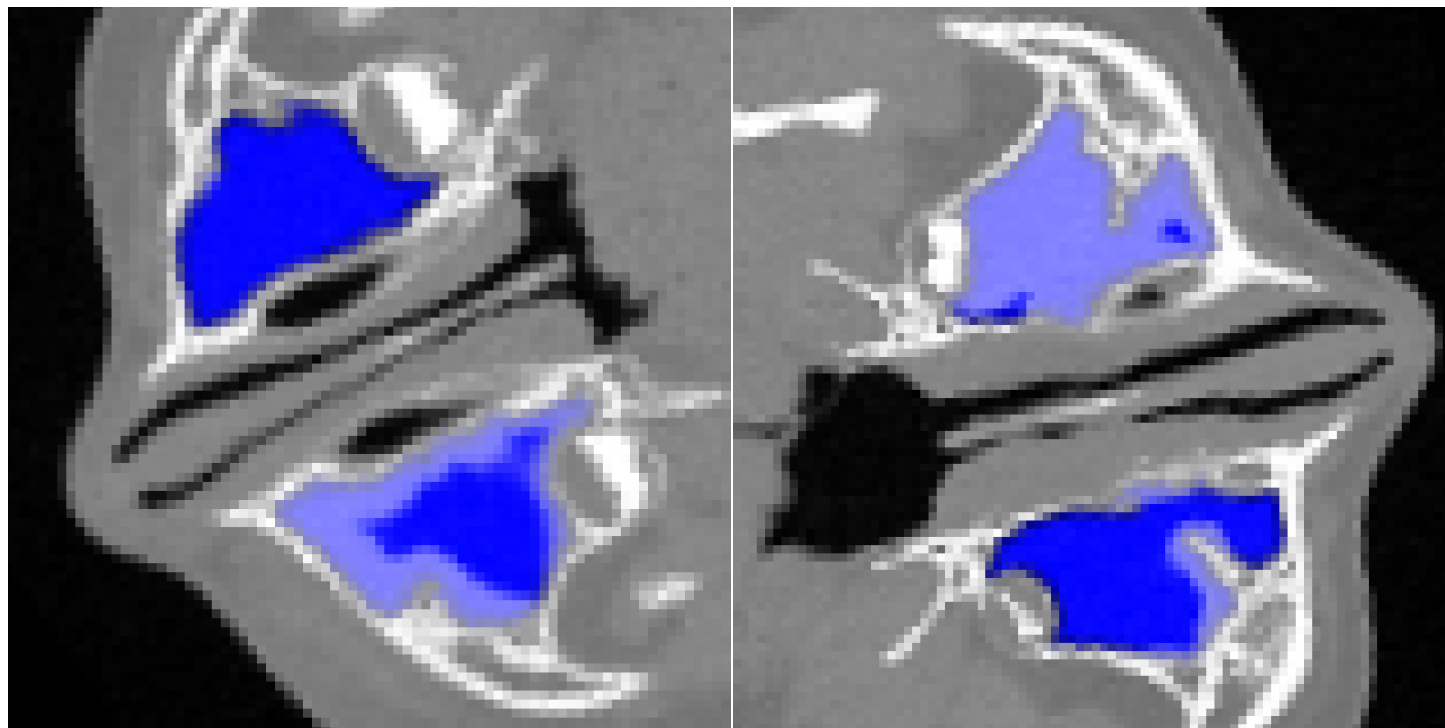


Path	0	1	2	3
Receptive field	5^3	18^3	36^3	56^3
Output patch	1^3	2^3	4^3	8^3

- Each output voxel receives information at 4 spatial scales
- 5^3 ensures voxel-level precision while 56^3 provides broad context
- Each receptive field is as centered at the output voxel as possible



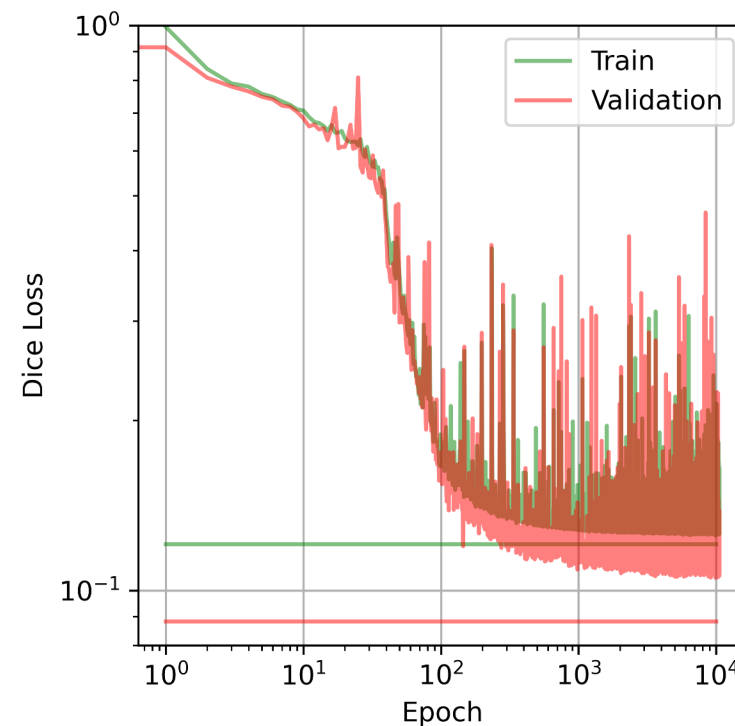
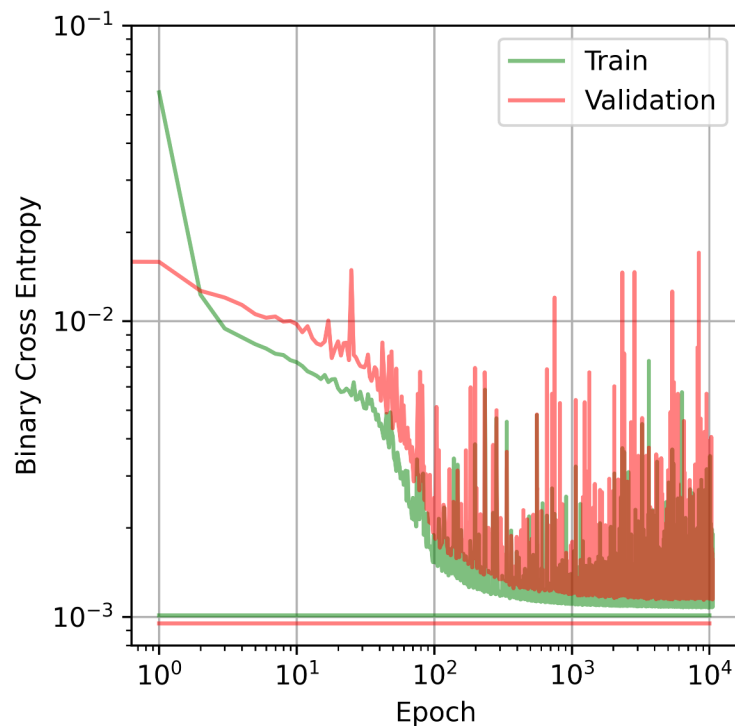
Data augmentation



- Random translations and arbitrary rotations about the body axis
- The model is trained to process scans at any axial orientation
- With fuzzy labels cross entropy and metrics have Shannon limits
- These limits are different for original and augmented images



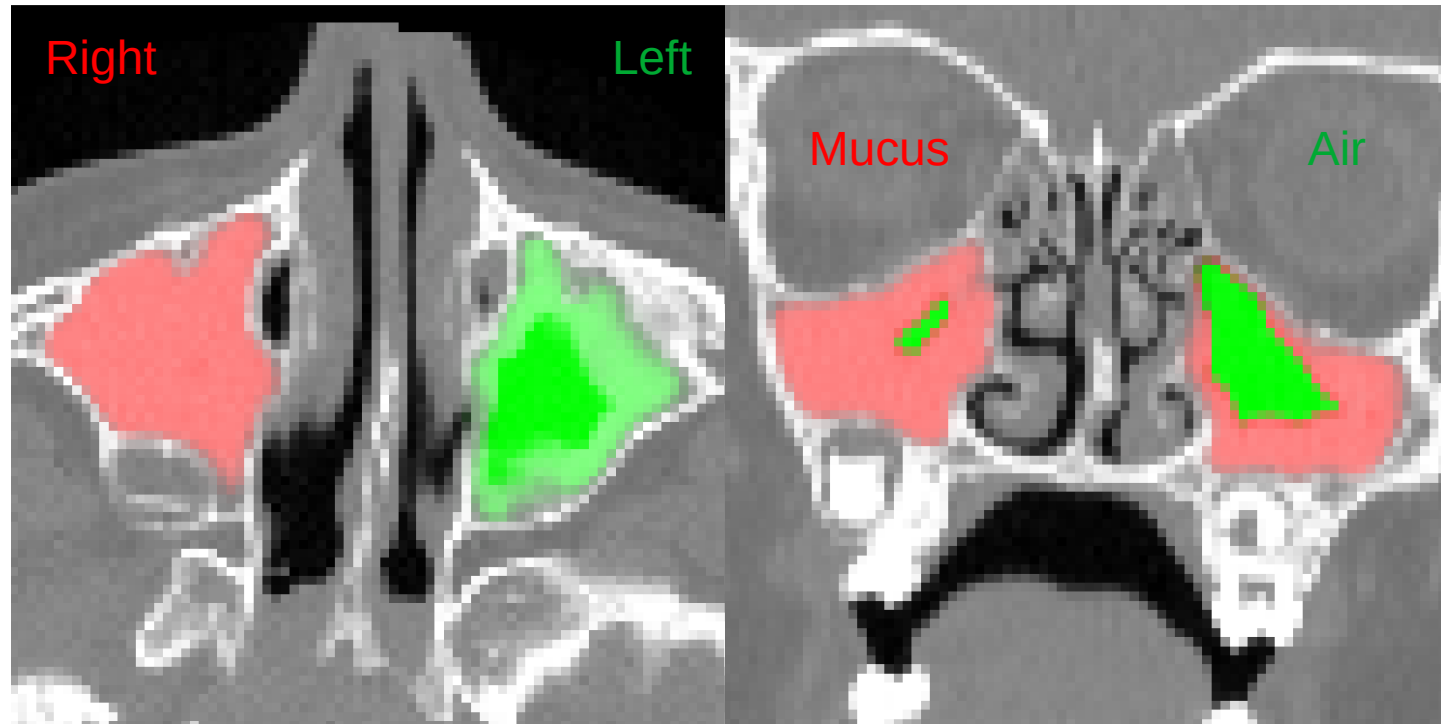
Training



- Pure cross-entropy because Dice tends to yield hard labels
- About 15 hours per 1000 epochs on a single gaming-class GPU
- About 10.000 epochs or 6.25 days needed for best results



Performance



- Sinus volume RMSE is 0.5 cm^3 with an average volume of 12 cm^3
- Involvement fraction RMSE is 1.5 percentage points
- Prediction takes a few seconds on CPU



Publication of the previous version



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A machine-learning model for quantitative assessment of maxillary sinus volume and involvement in children based on computed tomography

Algorytm uczenia maszynowego do automatycznej oceny objętości i stopnia zajęcia
zatok szczękowych u dzieci na podstawie badań tomografii komputerowej

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