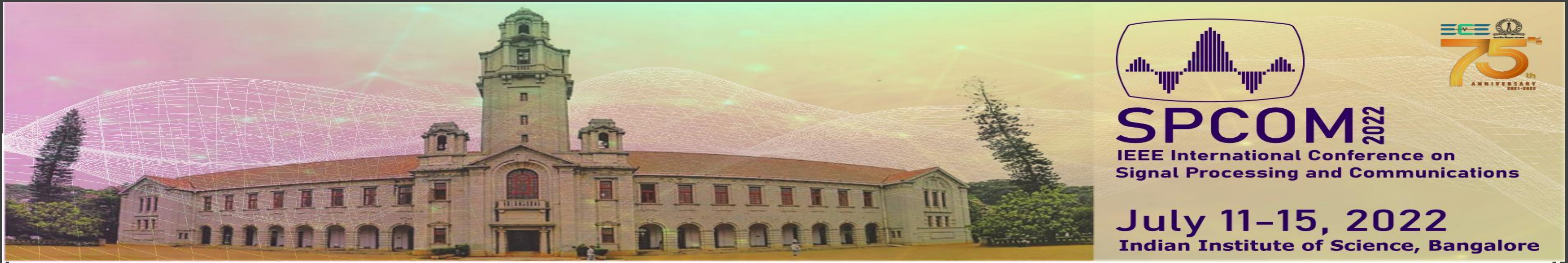

Modified U-Net Based Covid-19 Lesion Segmentation Using CT Scans

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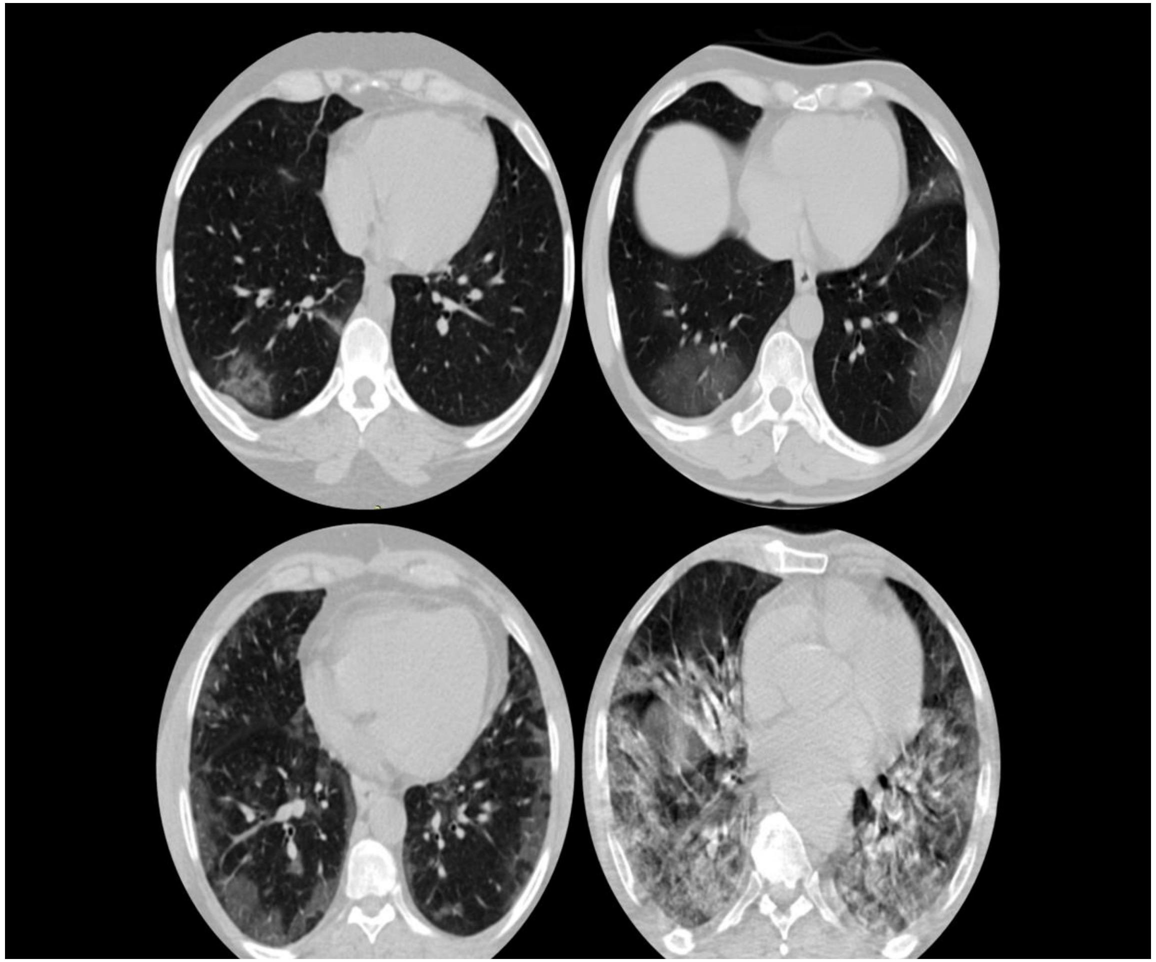
Mphasis FOUNDATION
INNOVATE • INCLUDE • IMPACT

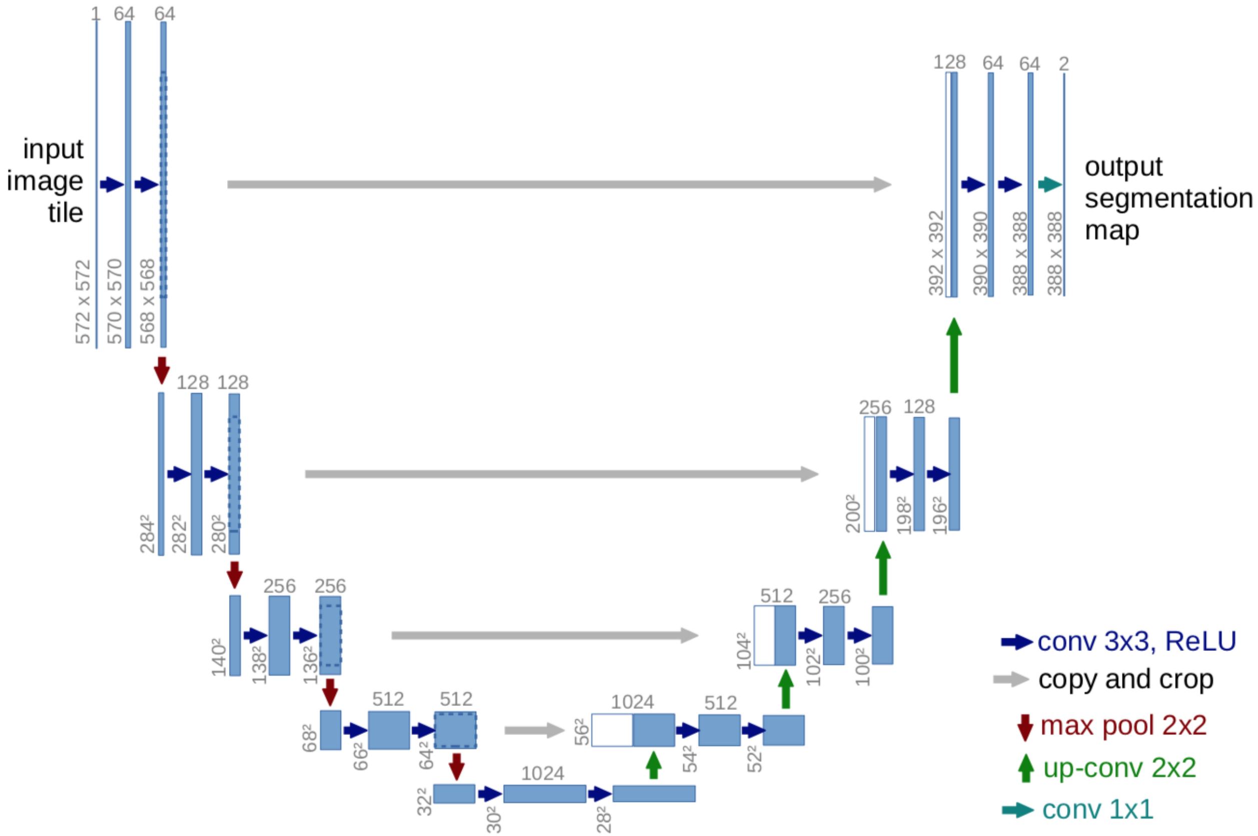
Covid-19 Lesions – CT Scans

- Lesions Detection & Segmentation – Extend and Severity of the disease
- Manual Segmentation of lesion CT – Tedious
- Objective → Automated Segmentation of lesions in CT slices
  - 2D framework – Less computational complexity



Model Architecture

Base framework of U-Net framework

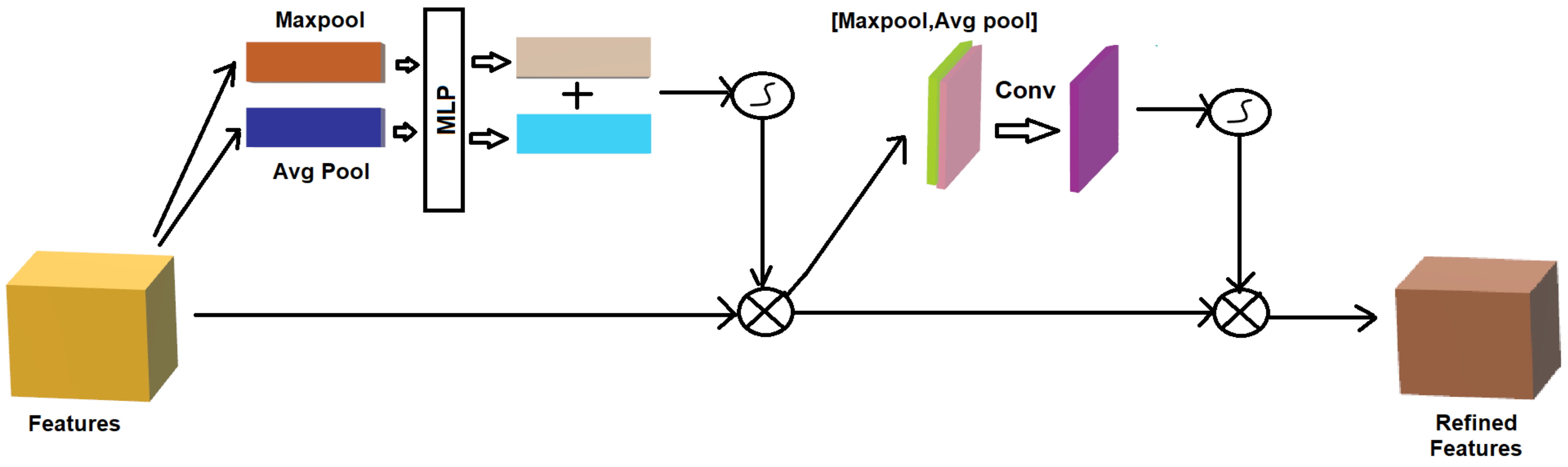


Model Architecture

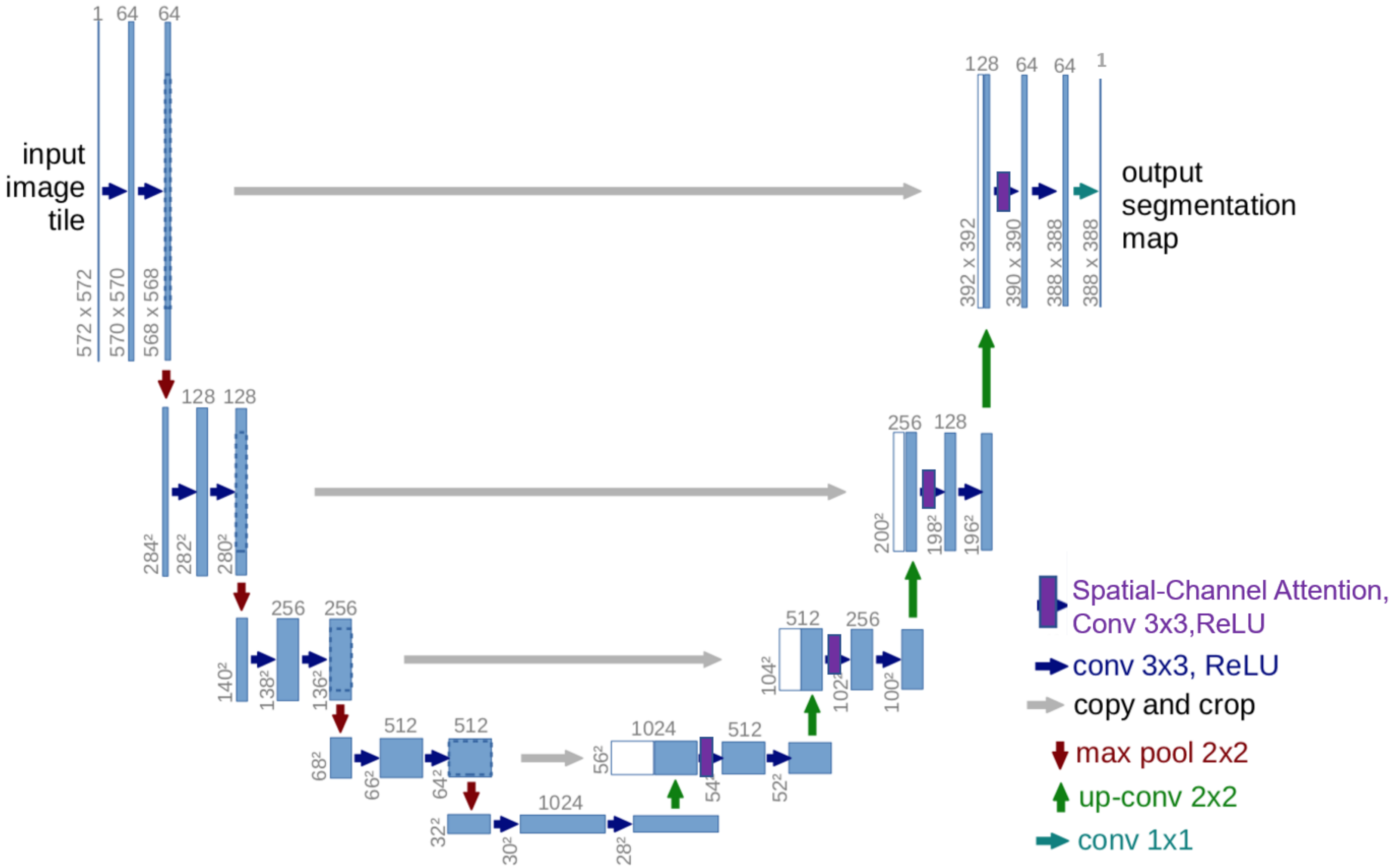
Base framework of U-Net framework

Spatial-channel attention modules (contextual relationships)

- Mechanism infused at different stages of the decoder after concatenation of transposed convolution output with cropped features from encoder part
- Have an effective localization by enabling the network to learn channel and spatial interdependencies of the concatenated feature map



Model Architecture



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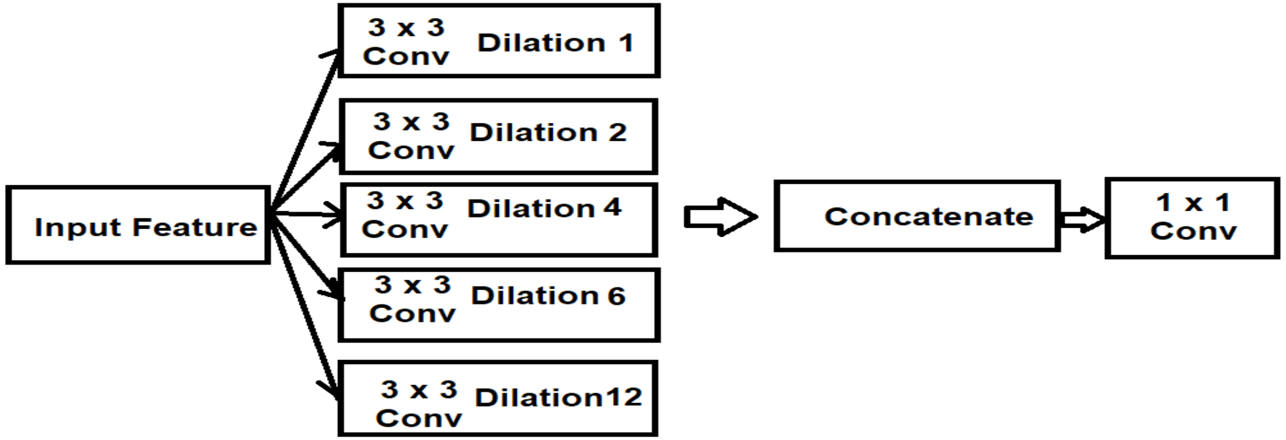
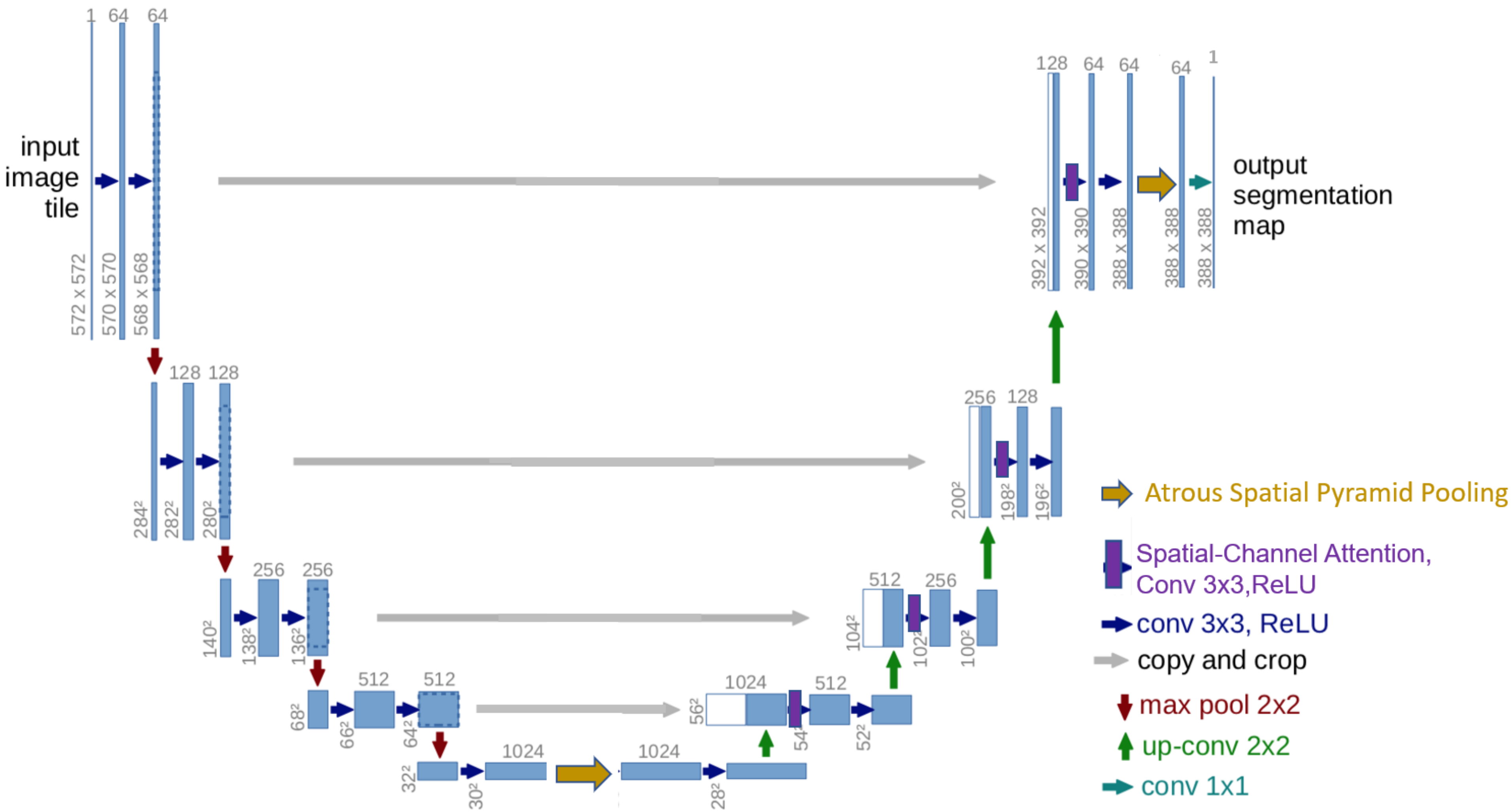
Atrous Spatial Pyramid Pooling modules (a wider receptive field)

- After the bottleneck layer and before the final output layer to provide a wider receptive field leading to improved localization of lesions



Model Architecture



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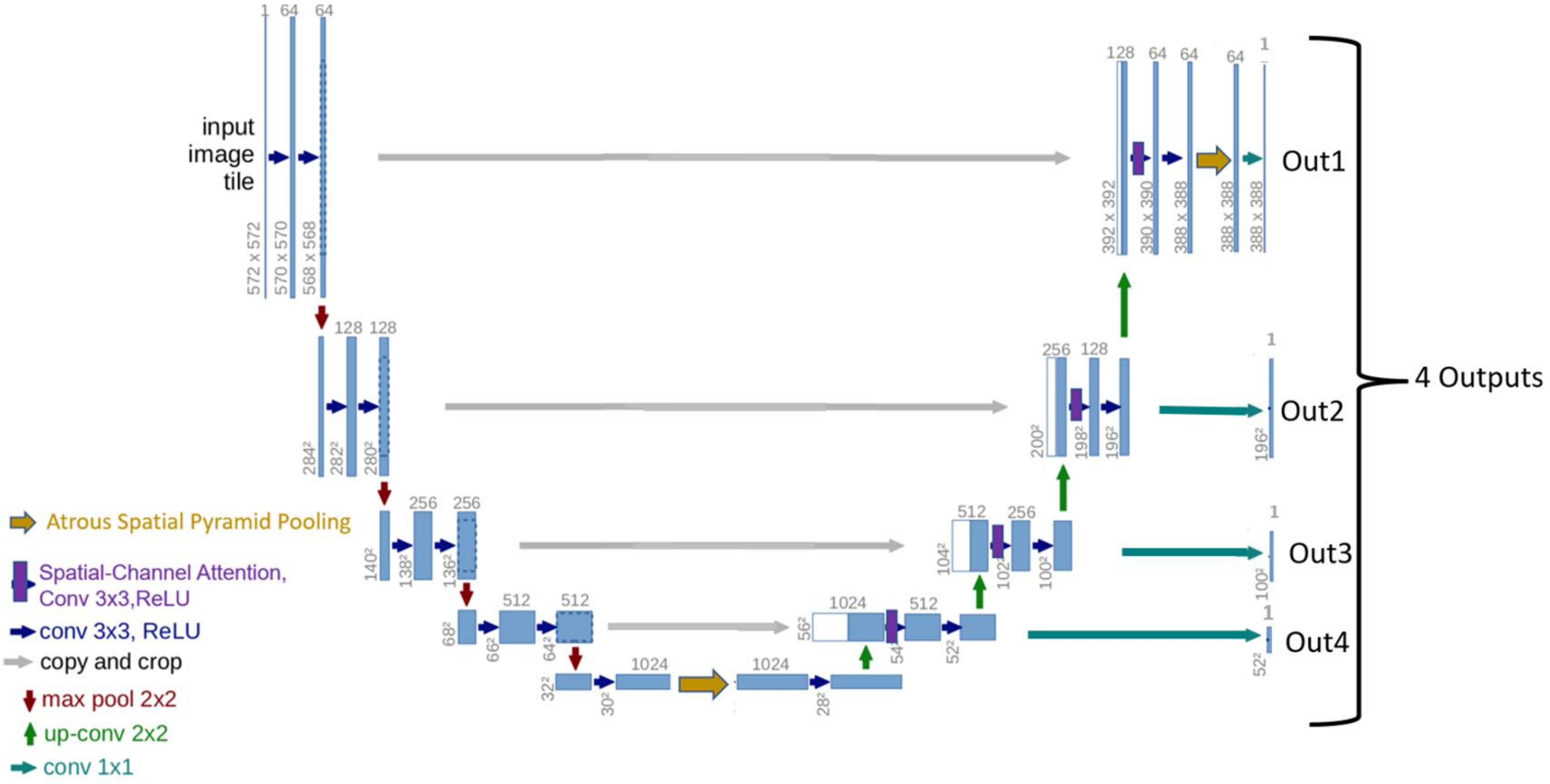
Deep Supervision (lesion focus, less error propagation)

- At different stages of decoder path
- Helps prevent error propagation from lower layers of decoders to higher layers and help in tuning the lower layers of decoderto focus on the lesions

Model Architecture



Overall Loss function

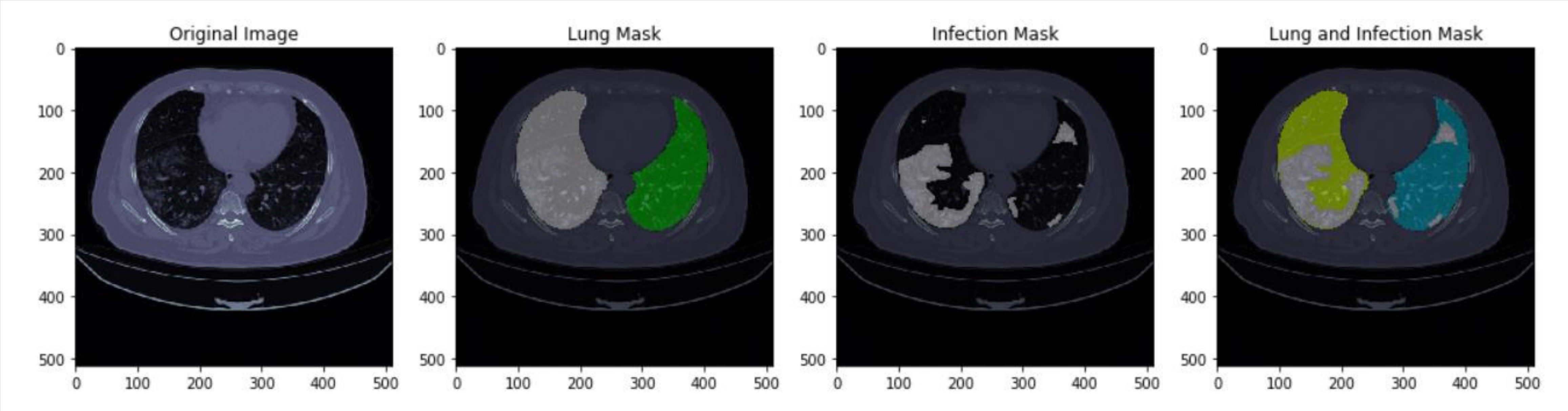
- Focal Tversky loss

- Overall Loss = 0.5* D1 + 0.2 * D2 + 0.2*D3 + 0.1*D4
- D1 – TL of Final output (Out1) of the model
- D2 – FTL of Out2
- D3 – FTL of Out3
- D4 – FTL of Out4

COVID-19 CT Lung and Infection Segmentation Dataset

- Two data → .nii
  1) Coronacases – 512*512 (160~250 slices)
  2) Radiopedia – 630*630 (60~160 slices)

- Labels : a) right lung, left lung
  b) infection



MOSMED CT-Scan data (Russian database)

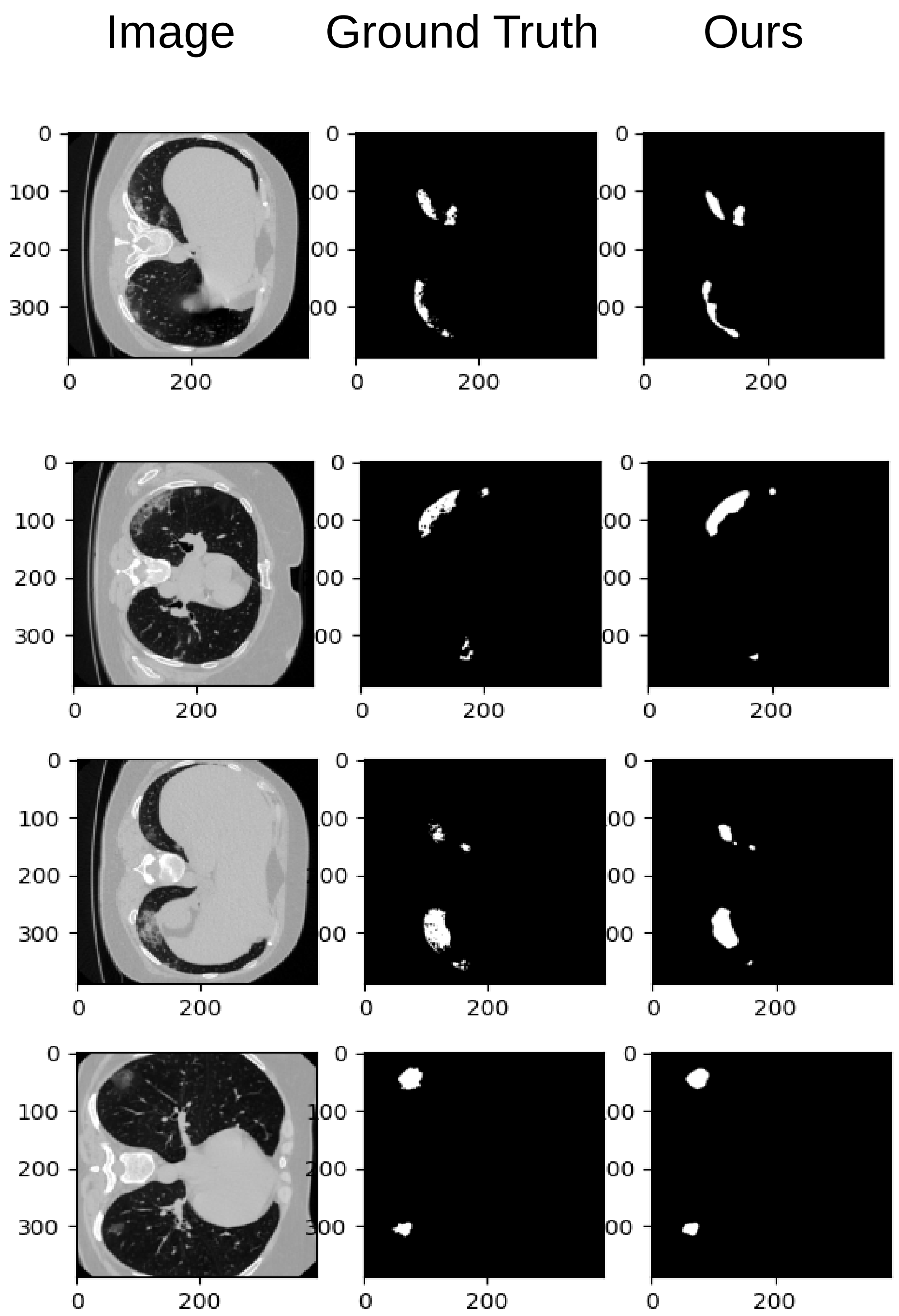
- MOSMED data → .nii format, 1100 subjects
  - CT-0 : Normal CT scan of 254 subjects
  - CT-1 : 684 positive subjects with Ground Glass Opacity (GGO), <25% involvement of lung parenchyma (50 subjects annotated for lesions)
  - CT-2 : 125 positive subjects with GGO, 25% - 50% involvement of lung parenchyma
  - CT-3 : 45 positive subjects with GGO and consolidation, 50%-75% involvement of lung parenchyma
  - CT-4 : 2 positive subjects with GGO, Consolidation and reticular changes, >75% involvement of lung parenchyma

Literature Results on Mosmed data

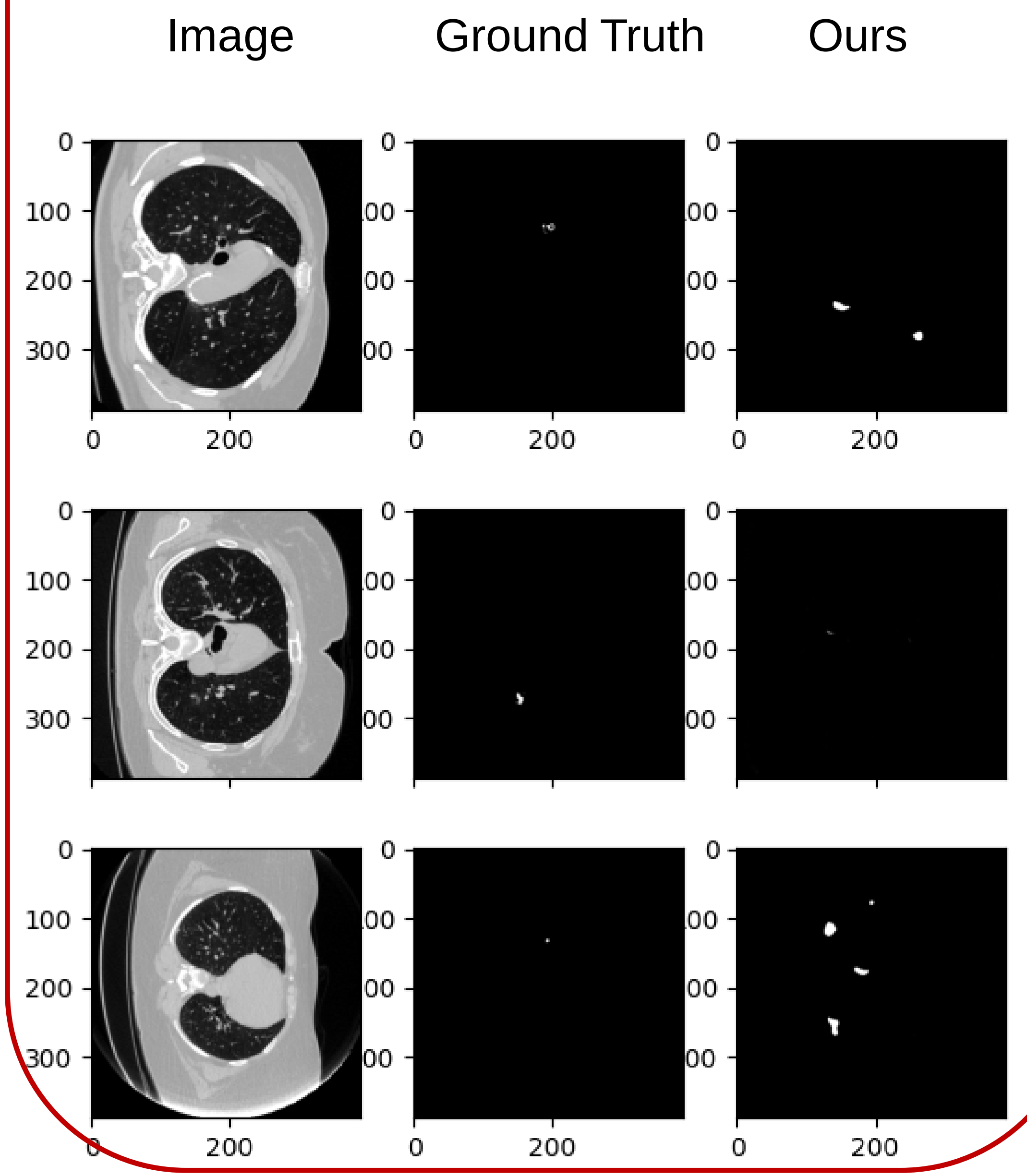
- Challenges – too small lesions, easily missed by most algorithms
- Limited works test on Mosmed data due to its difficult to segment lesions

Literature	Method	Dice Score
Bressem, et al	3D U-Net + pretrained encoder Resnet18	0.40
Lizzi, et al	3D U-Net + active contour lung segmentation	0.42
Zhang, et al	CoSinGAN	0.47

- All images are contrast adjusted
- Augmentation:
  - Horizontal and vertical flip
  - Rotation 90 (Clockwise/anti-clockwise)



Failed Cases



Abalation Studies

Network	Mean Dice Score
Unet + Attn	0.52
Unet+Attn+ASPP	0.54
Unet + Attn+DS	0.55
Ours (Unet+Attn+ASPP+DS)	0.57

Weights in Loss Function

- 0.5 * D1 + 0.2* D2 + 0.2* D3 + 0.1* D4 → Dice Score of 0.57
- 0.25 * D1 + 0.25* D2 + 0.25* D3 + 0.25* D4 → Dice Score of 0.51
- 0.9 * D1 + 0.05* D2 + 0.03* D3 + 0.02* D4 → Dice Score of 0.55

Comparison with other works

Literature	Method	Dice Score
Bressem, et al	3D U-Net + pretrained encoder Resnet18	0.40
Lizzi, et al	3D U-Net + active contour lung segmentation	0.42
Zhang, et al	CoSinGAN	0.47
Proposed	**U-Net + Attention+ASPP + Deep Supervision**	**0.57**

Conclusion

- Work presents a U-Net based segmentation framework incorporating Spatial-Channel Attention to extract rich contextual information and Atrous Spatial Pyramid Pooling to provide a wider receptive field to enhance localization of lesions.
- Deep Supervision is used to tune the decoder to focus on the lesions.
- Mean Dice score of 0.57 → effectiveness of the framework in segmenting hard ROIs of Mosmed data.
- The framework needs to be analyzed further using patch based and volumetric segmentation to improve the overall performance.

Thank You