Deep Learning for Pneumothorax Segmentation

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29 March 2020

Summary

Summary

Pneumothorax

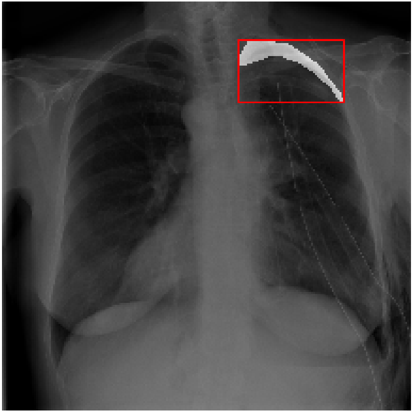


Figure – Example of a positive sample. The pneumothorax area is highlighted.

Summary

SIIM-ACR Pneumothorax Segmentation dataset

- 12000 chest radiographic images of size 1024×1024
- $y = 1$ if the patient has pneumothorax and $y = 0$ otherwise
- On regions where the pneumothorax is located, the pixels i have a label $y_i = 1$, else $y_i = 0$
- Down-sampled to 2669 images of each class
- Images resized 256×256

U-Net Baseline Architecture

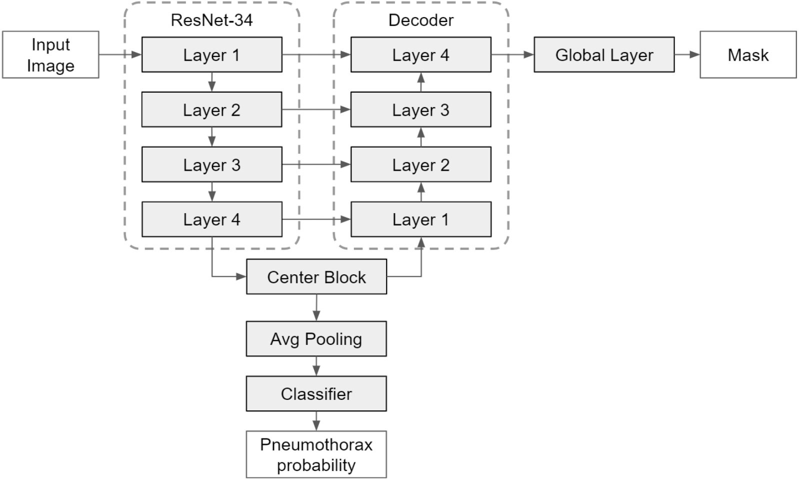


Figure – The baseline U-Net architecture.

Training Setup

	Parameter	Value
Global	Batch size	32
	Classification loss	BCE
	Segmentation loss	BCE
	λ_{cls}	0.1
Stage 1	Epochs	3
	Learning rate	5e-4
	Minimal learning rate	1e-4
Stage 2	Epochs	40
	Learning rate	5e-4
	Minimal learning rate	5e-5

Table – Main baseline hyperparameters

Summary

Lovász Loss - Description

Key idea

The *Lovász loss* [2] is a **tractable surrogate** for the **optimisation of the Jaccard distance** $d_J(A, B)$ in neural networks. It smoothly extends it to continuous values of $\mathbb{R}^+$.

- Uses results from **submodular analysis**.
  A set function $\Delta : \{0,1\}^N \to \mathbb{R}$ is *submodular* if for all $\mathbf{A}, \mathbf{B} \in \{0,1\}^N$:

$$\Delta(\mathbf{A}) + \Delta(\mathbf{B}) \geq \Delta(\mathbf{A} \cup \mathbf{B}) + \Delta(\mathbf{A} \cap \mathbf{B})$$

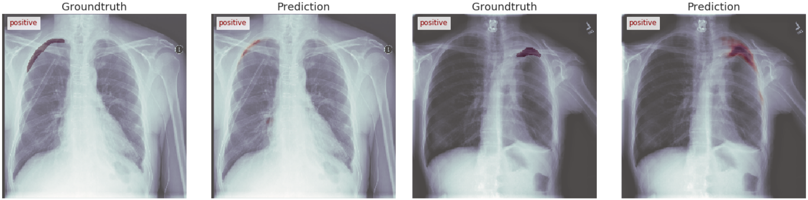
- $A \in \mathcal{P}(\{0,1\}^N) \mapsto d_J(A, B)$ is a submodular function

Lovász Loss - Description

- A natural way to extend d_J to continuous values is to consider its **convex closure**. In general, NP-Hard...
- The *Lovász extension* [1] makes it **polynomial time**
- Composed of differentiable operations efficiently implemented on a GPU

Table – Influence of using Lovász and BCE losses with the baseline architecture.

Setup	λ_{cls}	Dice	Accuracy
Baseline (BCE)	0.1	0.583	0.828
Lovász	0.01	**0.588**	**0.832**

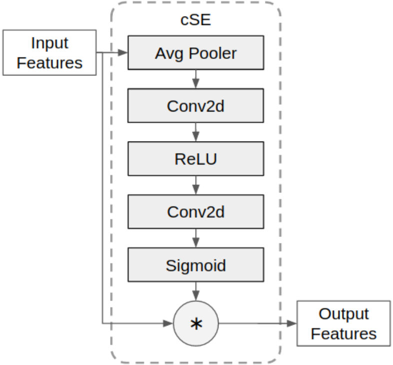


scSE -Description

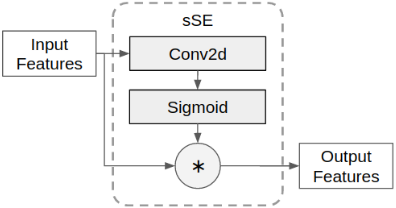
Key idea

Spatial and channel Squeeze & Excitation (scSE) [4] is a general module that combines a **spacial** and **channel recalibration** of any feature map

scSE - Description



(a) channel SE (cSE) block



(b) spatial SE (sSE) block

Figure – Architecture of the sSE and cSE blocks.

scSE - Description

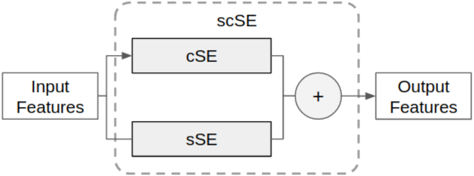
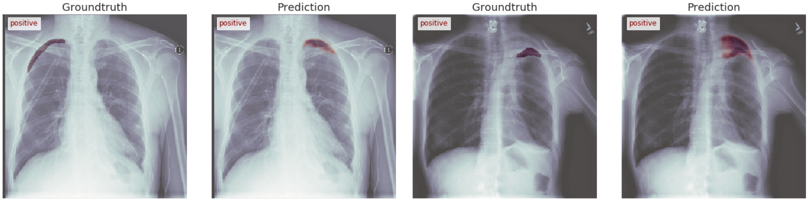


Figure – Architecture of the scSE module.

Table – Influence of using scSE in the U-Net decoder.

Setup	Dice	Accuracy
Baseline	**0.583**	0.828
scSE	0.578	**0.836**



ASPP - Description

Key idea

Atrous Spatial Pyramid Pooling (ASPP) is computationally efficient alternative to **Pyramid Pooling** that uses **multiple dilated convolutions** to deal with **multi-scale** object segmentation.

ASPP - Description

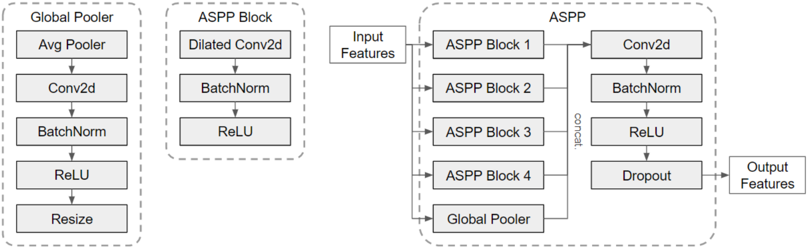


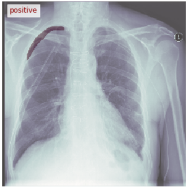
Figure – Architecture of the ASPP module and its components.

ASPP - Results

Table – Influence of using ASPP as the center U-Net block.

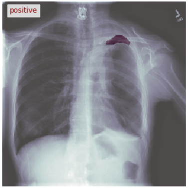
Setup	Dice	Accuracy
Baseline	0.583	0.828
ASPP	**0.592**	**0.838**

Groundtruth



Prediction

Groundtruth



Prediction

Hypercolumns - Description

Key idea

Hypercolumns [3] combine information from all stages of the decoder. The early stages, of **higher spacial resolution**, are helpful for **fine-grained** tasks.

Hypercolumns - Description

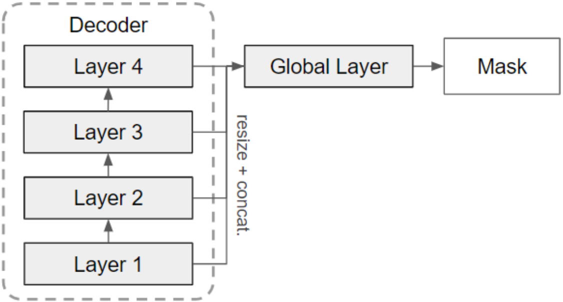
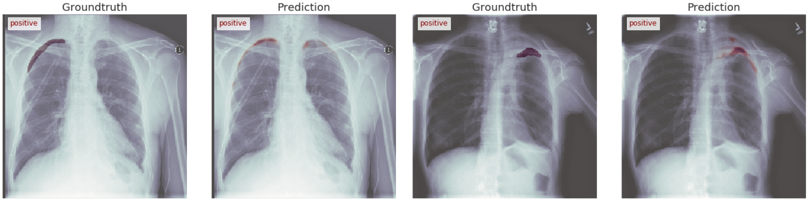


Figure – Adding hypercolumns to the decoder.

Hypercolumns - Results

Table – Influence of using hypercolumns in the U-Net architecture.

Setup	Dice	Accuracy
Baseline	0.583	0.828
Hypercolumns	**0.585**	**0.842**



Summary

Ablation Study

Lovász	ASPP	Hypercolumns	scSE	Dice	Accuracy
				0.583	0.828
✓				0.588	0.832
	✓			0.592	0.838
		✓		0.585	**0.842**
			✓	0.578	0.836
✓	✓			0.574	0.829
✓		✓		0.586	0.829
✓			✓	0.582	0.835
	✓	✓		**0.593**	0.837
	✓		✓	0.588	0.827
		✓	✓	0.579	0.836
✓	✓	✓		0.579	0.832
✓	✓		✓	0.585	0.836
✓		✓	✓	0.578	0.834
	✓	✓	✓	0.574	0.840
✓	✓	✓	✓	0.574	0.837

Conclusion

We review 4 methods applied alone and combined.

- **ASPP** and **Hypercolumns** works well alone and together
- **Lovász** works only alone
- **scSE** consistently deteriorates the dice

Insights :

- The improvements are *lower than expected* from papers
- Using multiple methods is often *worse than using a single one*

Thank you for your attention !

[1] Francis Bach et al.

Learning with submodular functions : A convex optimization perspective.

Foundations and Trends® in Machine Learning, 6(2-3) :145–373, 2013.

[2] Maxim Berman and Matthew B. Blaschko.

Optimization of the jaccard index for image segmentation with the lovász hinge.

CoRR, abs/1705.08790, 2017.

[3] Bharath Hariharan, Pablo Arbeláez, Ross Girshick, and Jitendra Malik.

Hypercolumns for object segmentation and fine-grained localization, 2014.

[4] Abhijit Guha Roy, Nassir Navab, and Christian Wachinger.

Recalibrating fully convolutional networks with spatial and channel 'squeeze & excitation' blocks.

CoRR, abs/1808.08127, 2018.