Paper Presentation by Gary Yang of Group 9

U-Net: Convolutional Networks for Biomedical Image Segmentation

&

3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation

Ronneberger O, Fischer P, Brox T. U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical image computing and computer-assisted intervention 2015 Oct 5 (pp. 234-241). Springer, Cham. https://arxiv.org/pdf/1505.04597.pdf

Çiçek Ö, Abdulkadir A, Lienkamp SS, Brox T, Ronneberger O. 3D U-Net: learning dense volumetric segmentation from sparse annotation. In International conference on medical image computing and computer-assisted intervention 2016 Oct 17 (pp. 424-432). Springer, Cham. https://arxiv.org/pdf/1606.06650.pdf

Project Overview

Team 9 - predicting hemorrhage-related outcomes with CT volumetry for traumatic hemothorax.

- Data: axial CT scans.
- Preprocessing: crop + resize
- Goal: train deep neural networks that can automatically segment scans.
- Evaluation: Dice score; volume correlation; visual inspection

Why Choose these Papers?

3D U-Net is

- Influential models.
- Necessary for baseline
- Core of many state-of-the-art models.

U-Net is

- Core to 3D U-Net

Summary

U-Net paper

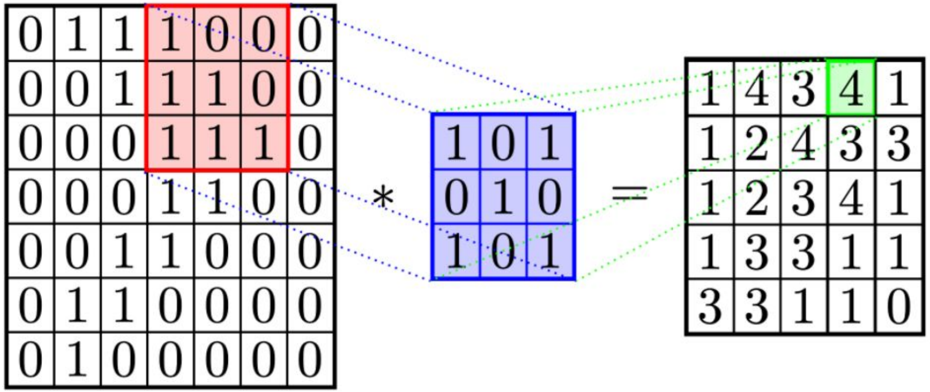
- A *time-efficient* deep network that utilizes *few training instances* for *segmentation tasks*.

3D U-Net paper

- A deep neural network model that can handle *partially labelled* volumetric data sets.

Vocabularies

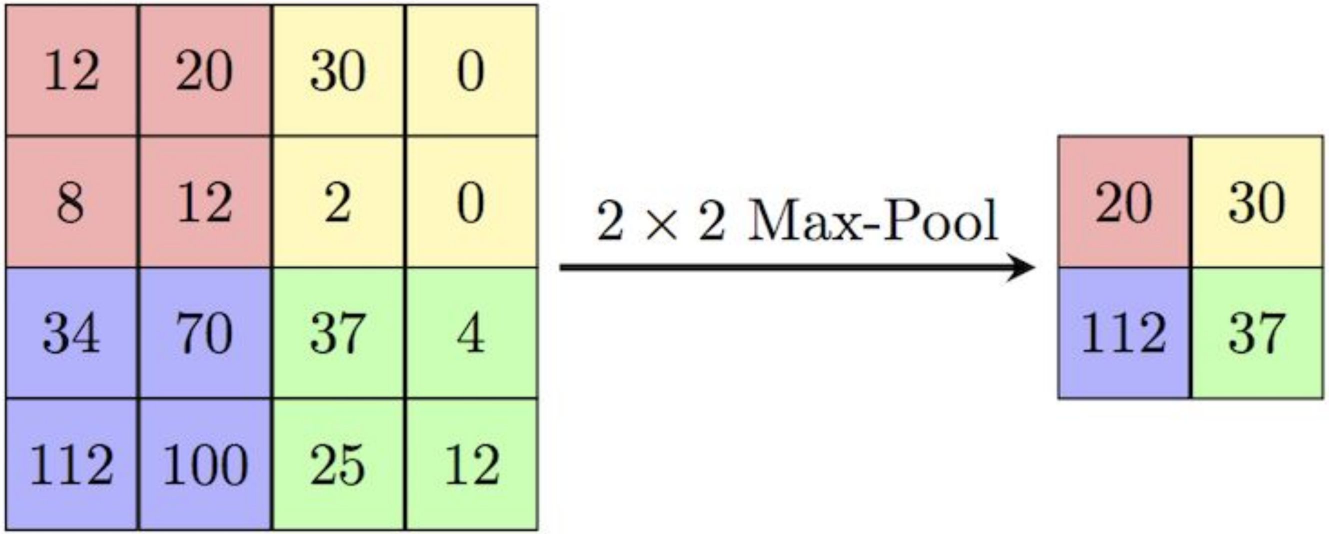
- Convolution: A matrix to matrix element-wise multiplication, followed by an overall summation.
- Context: The values of surrounding elements. Help models produce a more informed answer.



https://tex.stackexchange.com/questions/522118/visualizing-matrix-convolution

Vocabularies

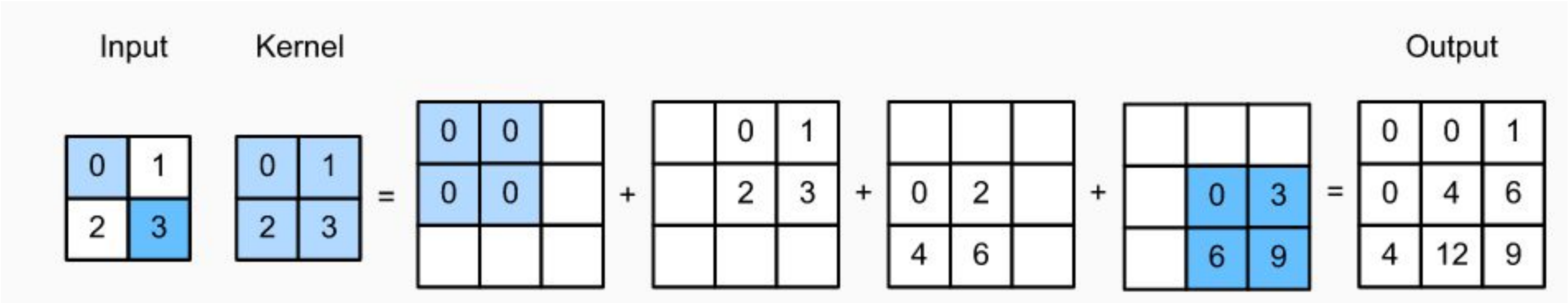
- Max pool: An operation that selects the greatest value within the region of interest.



https://computersciencewiki.org/index.php/File:MaxpoolSample2.png

Vocabularies

- Transposed convolution: A reversed convolution that up-samples. Multiple of the kernel filter matrix summed in a sliding window fashion.



https://towardsdatascience.com/transposed-convolution-demystified-84ca81b4baba

Vocabularies

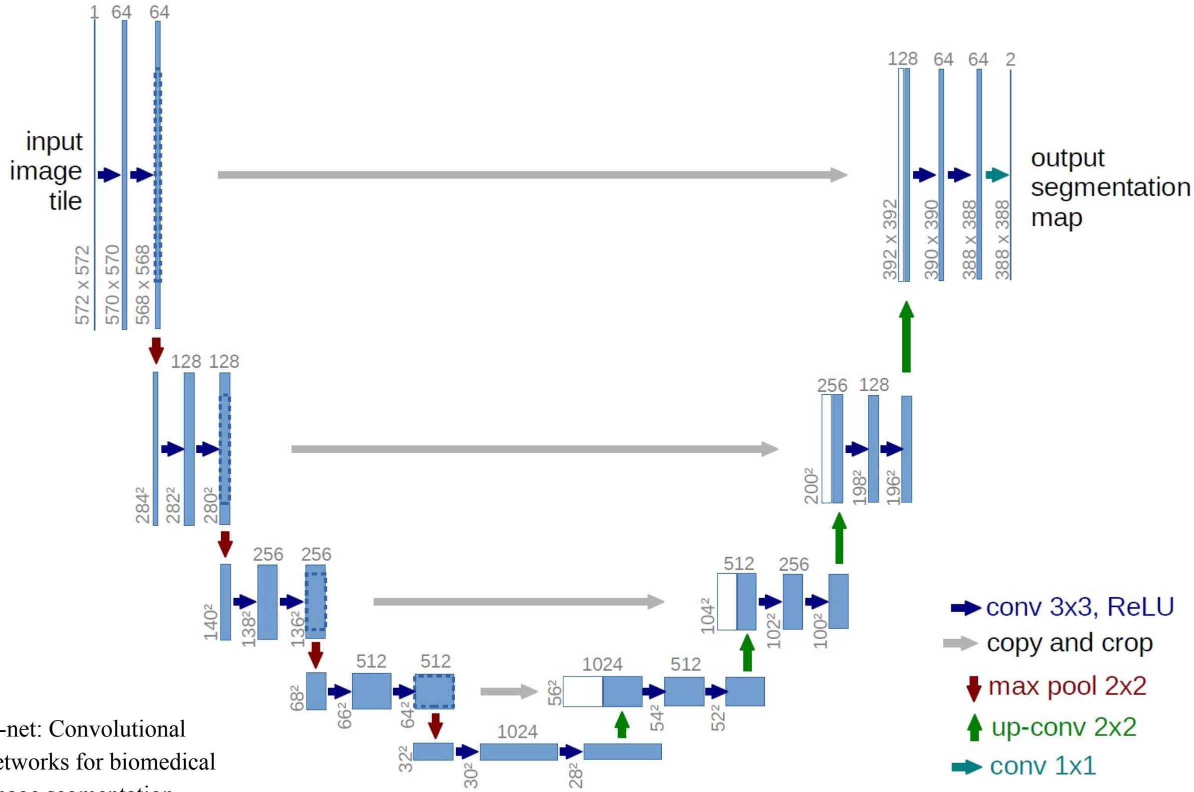
- Data augmentation: Increase the # of examples by performing rigid transformations, and elastic deformable transformations, etc. It allows the model to learn the invariant features within images

- Batch Normalization: pixel-wise normalization across all matrices in the batch.

Vocabularies

- Encoder: Transformation from the image frame to an unknown frame
- Decoder: Transformation from an unknown frame back to the original image frame.

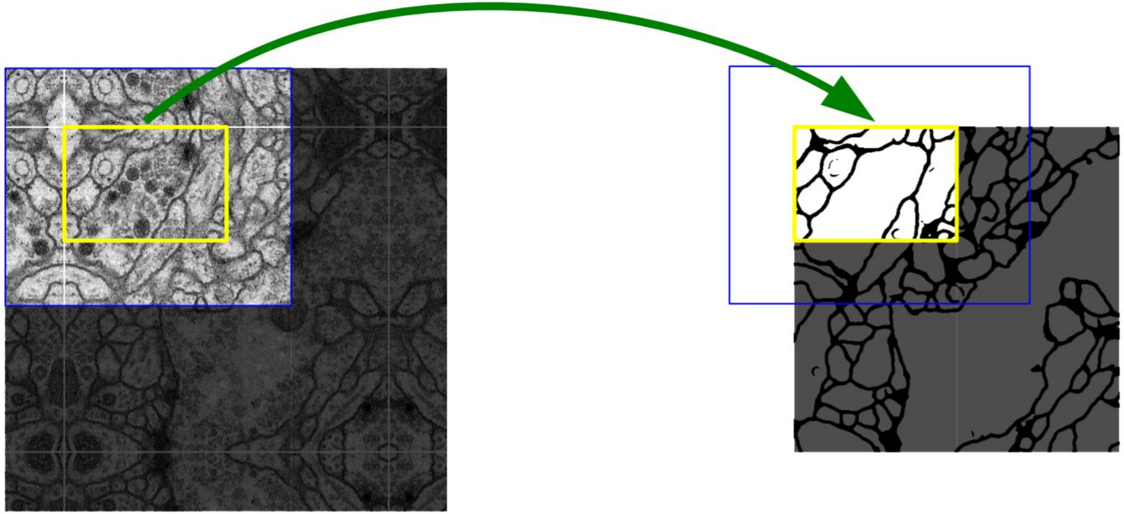
Implementations



U-net: Convolutional networks for biomedical image segmentation.

- Encoder: condensed information over broad range. More “what” & reduced “where”
- Decoder: Localization of pixel labeling.
- Concatenation aids the localization step

Implementations

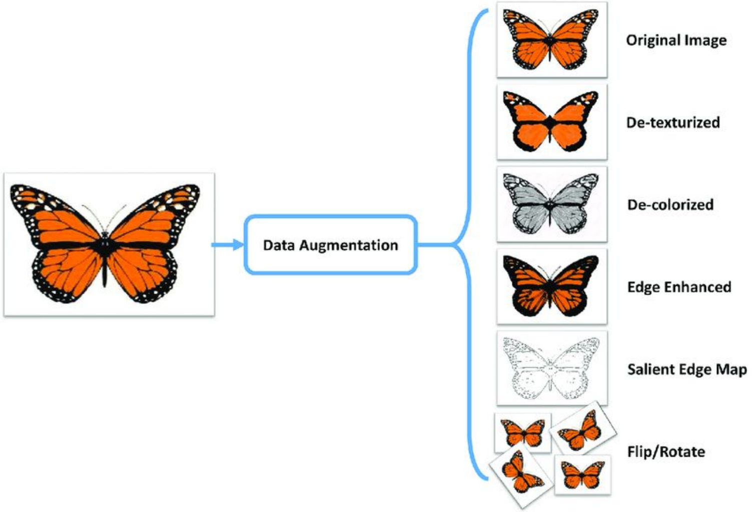


- Mirror padding to ensure context for corner pixels

U-net: Convolutional networks for biomedical image segmentation.

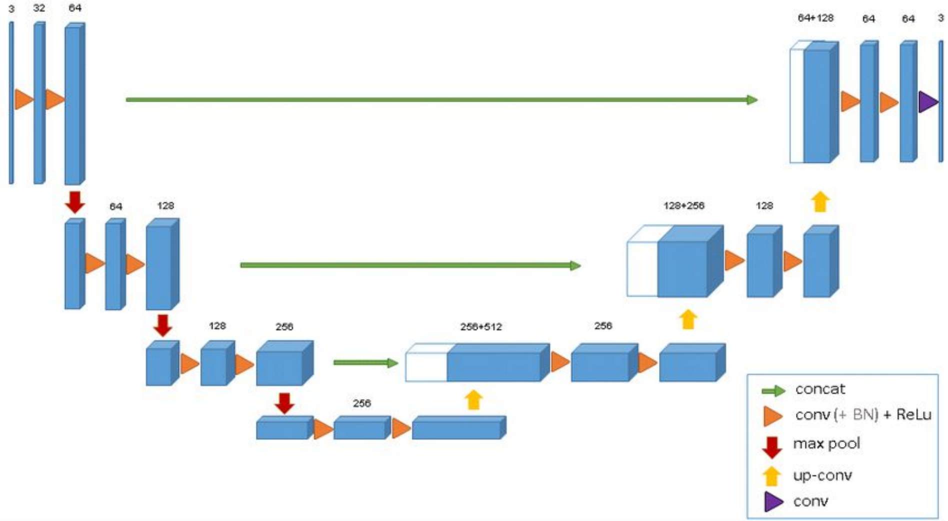
Implementations

- Data-Augmentation



https://medium.com/secure-and-private-ai-writing-challenge/data-augmentation-increases-accuracy-of-your-model-but-how-aa1913468722

- 3D U-Net



3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation

Results

2D

Table 1. Ranking on the EM segmentation challenge [14] (march 6th, 2015), sorted by warping error.

Rank	Group name	Warping Error	Rand Error	Pixel Error
	** human values **	0.000005	0.0021	0.0010
1.	u-net	**0.000353**	0.0382	0.0611
2.	DIVE-SCI	0.000355	0.0305	0.0584
3.	IDSIA [1]	0.000420	0.0504	0.0613
4.	DIVE	0.000430	0.0545	**0.0582**
⋮				
10.	IDSIA-SCI	0.000653	**0.0189**	0.1027

Table 2. Segmentation results (IOU) on the ISBI cell tracking challenge 2015.

Name	PhC-U373	DIC-HeLa
IMCB-SG (2014)	0.2669	0.2935
KTH-SE (2014)	0.7953	0.4607
HOUS-US (2014)	0.5323	-
second-best 2015	0.83	0.46
u-net (2015)	**0.9203**	**0.7756**

U-net: Convolutional networks for biomedical image segmentation.

3D

Table 1: Cross validation results for semi-automated segmentation (IoU)

test slices	3D w/o BN	3D with BN	2D with BN
subset 1	0.822	0.855	0.785
subset 2	0.857	0.871	0.820
subset 3	0.846	0.863	0.782
average	0.842	0.863	0.796

3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation

Good

- Novel attempts at the time

Criticism

- Vague explanations of metrics

Table 1. Ranking on the EM segmentation challenge [14] (march 6th, 2015), sorted by warping error.

Rank	Group name	Warping Error	Rand Error	Pixel Error
	** human values **	0.000005	0.0021	0.0010
1.	u-net	**0.000353**	0.0382	0.0611
2.	DIVE-SCI	0.000355	0.0305	0.0584
3.	IDSIA [1]	0.000420	0.0504	0.0613
4.	DIVE	0.000430	0.0545	**0.0582**
⋮				
10.	IDSIA-SCI	0.000653	**0.0189**	0.1027

- Wrong Premises for 3D U-Net

  "In many biomedical applications, only very few images are required to train a network that generalizes reasonably well. This is because each image already comprises repetitive structures with corresponding variation."

U-net: Convolutional networks for biomedical image segmentation.

Criticism

- Lack of Comparison w/ Other models

Table 1: Cross validation results for semi-automated segmentation (IoU)

test slices	3D w/o BN	3D with BN	2D with BN
subset 1	0.822	0.855	0.785
subset 2	0.857	0.871	0.820
subset 3	0.846	0.863	0.782
average	0.842	0.863	0.796

- (Side Note) Lack of Maintenance of U-Net & 3D U-Net

Relevance

- Benchmark
  - 0.366 ± 0.096 for the right lung hemothorax and 0.463 ± 0.104 for the left lung hemothorax
- Fail to provide high-resolution localization [1]
- Inadequate in addressing class imbalance problem

[1] Dreizin, D., Zhou, Y., Zhang, Y., Tirada, N., & Yuille, A. L. (2020). Performance of a Deep Learning Algorithm for Automated Segmentation and Quantification of Traumatic Pelvic Hematomas on CT. Journal of digital imaging, 33(1), 243–251. https://doi.org/10.1007/s10278-019-00207-1