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U-Net for brain tumor segmentation

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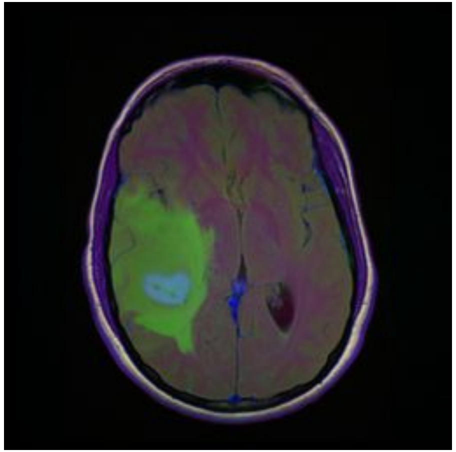
Brain Tumor segmentation

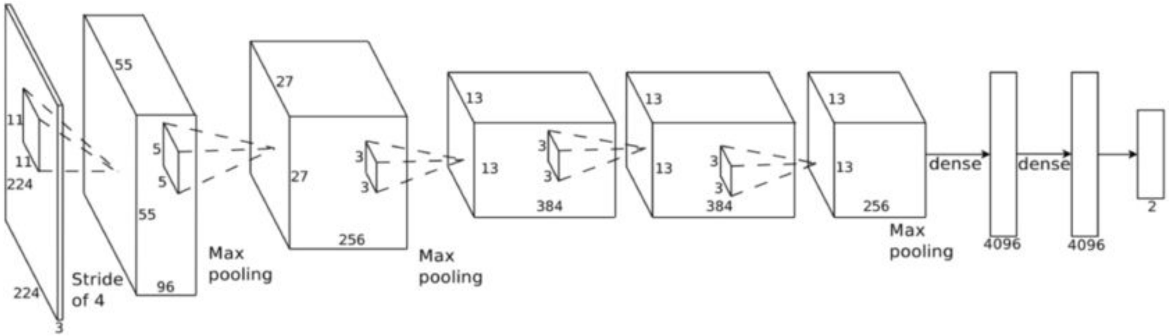
- In the United States 23.000 cases only in 2015;
- Difficult to segment due to the tentacle like structure;
- Deep learning vs Hand Crafted Machine learning model:
    - learning from the data;
    - exploit GPU computation;
    - faster for inferencing.



U-Net model

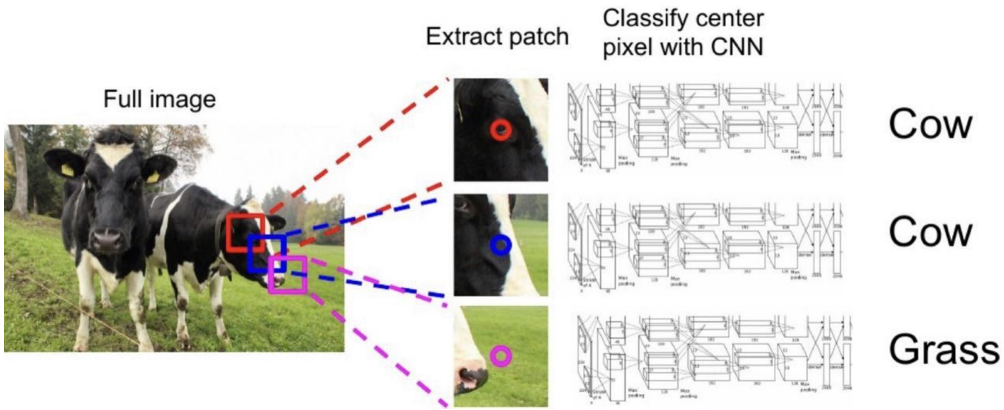
Convolutional Neural Networks

- Convolution;
- Non-linear activation;
- Pooling;
- Not designed for segmentation.

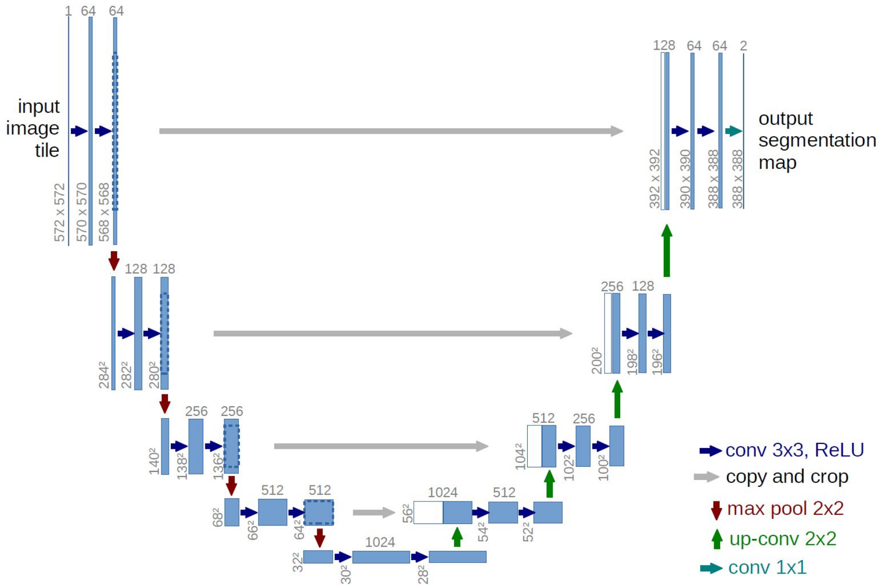


CNNs Image Segmentation

- Labelling of each pixel;
- First approach sliding window;
- Extremely slow;
- Reusing shared features.



U-Net model

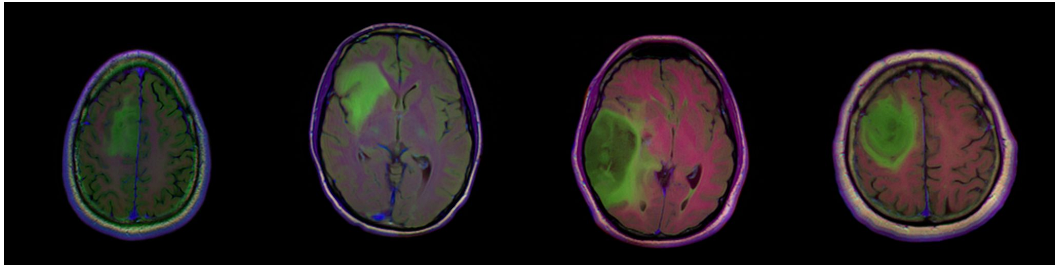


Main characteristics:

- Contractive and expansive parts;
- Transpose convolution;
- Skip connections;
- 1D convolution and Soft-max.

Experiments

Dataset

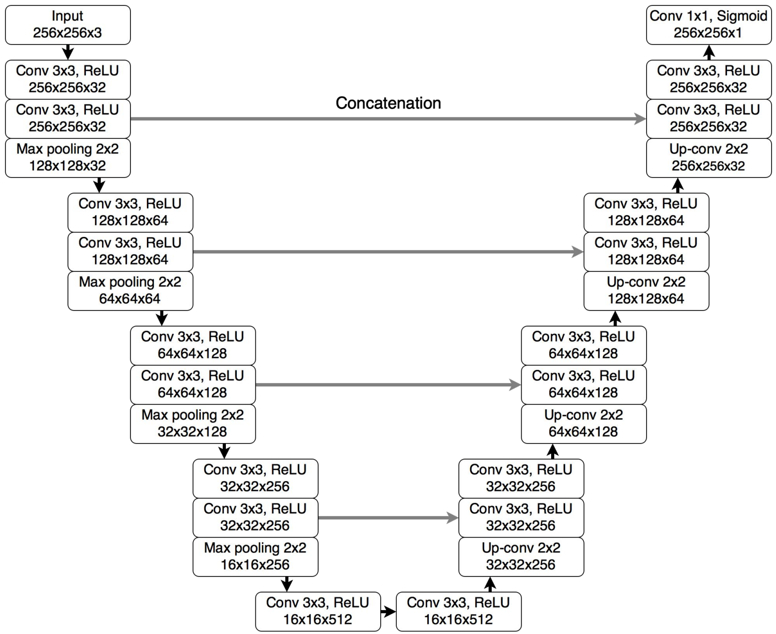


Lower-glade gliomas collection

1. 110 patients selected from 5 institutions;
2. Number of slices that varies from 20 to 88;
3. For each image a mask annotated by a radiologist;
4. Preprocessing: skull stripping and normalization;

Architectures and tuning

- Different input;
- Sigmoid activation function;
- Dice Similarity Coefficient;
- Batch Normalization;
- 22h of GPU computation;
- Optimizer: Adam PyTorch.



Results

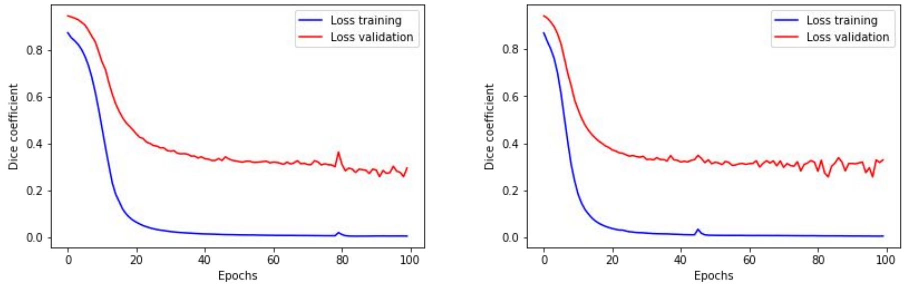
Learning curves batch normalization

#Epochs	Learning rate	Loss train	Loss validation
100	0.1	0.038945	0.358600
100	0.01	0.022355	0.297494
100	0.0001	0.006013	0.300957

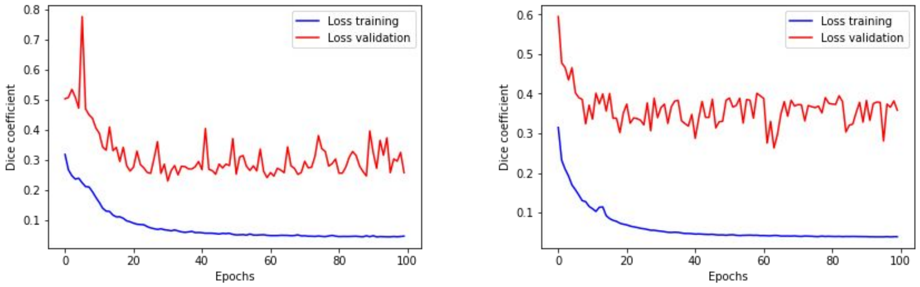
Values without Batch Normalization

#Epochs	Learning rate	Loss train	Loss validation
100	0.1	0.047595	0.257974
100	0.01	0.022803	0.349134
100	0.0001	0.004725	0.260191

Values with Batch Normalization



Learning curves with 0.0001 with and without Batch Normalization.

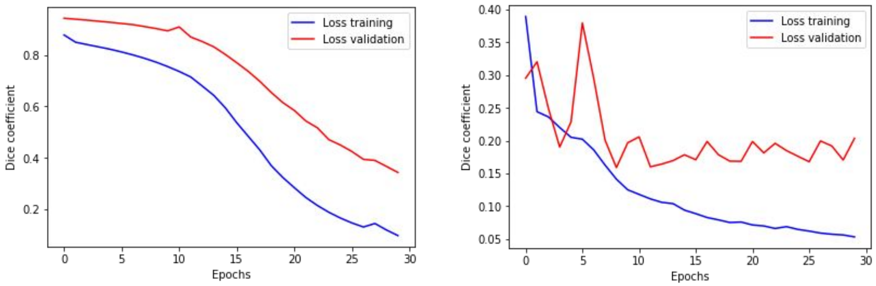


Learning curves with 0.1 with and without Batch Normalization.

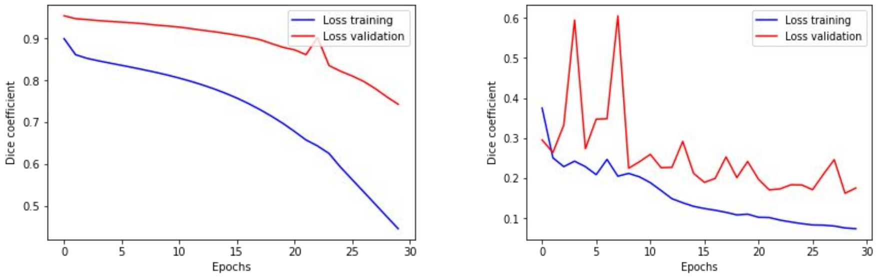
Learning curves batch size

Batch size	Learning rate	Loss train	Loss validation
16	0.0001	0.018764	0.341420
32	0.0001	0.097907	0.343338
64	0.0001	0.445822	0.742853
16	0.1	0.065286	0.262480
32	0.1	0.053285	0.203653
64	0.1	0.074282	0.175922

Varying the batch size with 30 epochs.

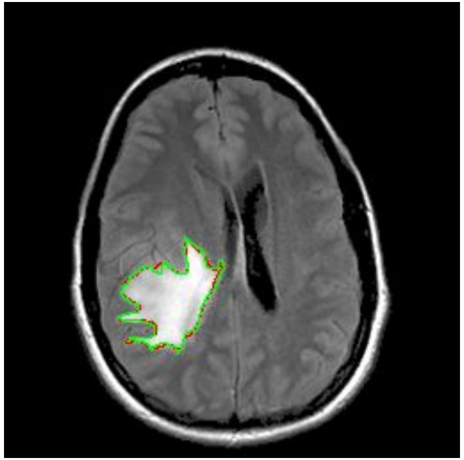


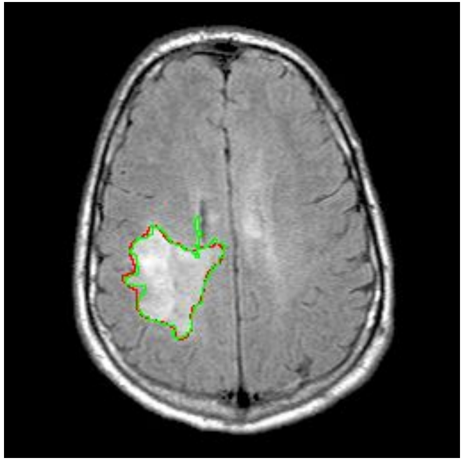
Learning rate of 0.0001 and 0.1 with batch size of 32 .



Learning rate of 0.0001 and 0.1 with batch size of 64 .

Masks predicted





Further improvements

- Training on more data;
- Try an ensemble of models;
- Apply denoising algorithms on the images;
- Try different hyperparameters configurations (more computational power).

Wrap up

- U-Net model
  - Breakthrough in medical image segmentation;
  - Can be used also for 3D Image segmentation;
  - A lot of research still going on image segmentation (for example Transformers, TransUNet).
- Experience
  - Understand the model;
  - Hyperparameters tuning is an art;
  - "A machine learning engineer needs GPU".

Bibliography

- M. Buda, A. Saha, and M. A. Mazurowski. Association of genomic subtypes of lower-grade gliomas with shape features automatically extracted by a deep learning algorithm.
- O. Ronneberger, P. Fischer, and T. Brox. U-net: Convolutional networks for biomedical image segmentation.
- A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks.
- S. Ioffe and C. Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift.
- I. Goodfellow, Y. Bengio, and A. Courville. Deep learning.

Figures

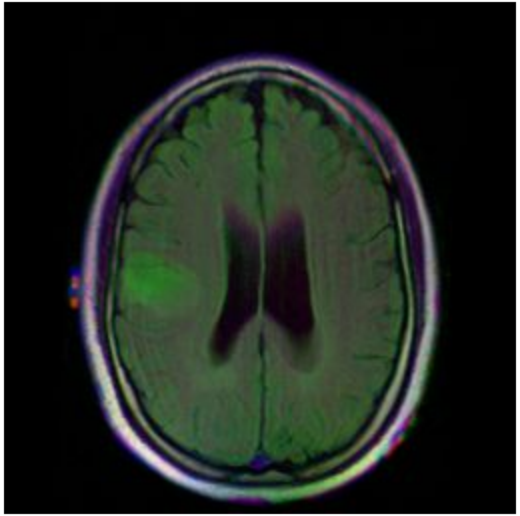
Slide 5: Imagenet classification with deep convolutional neural networks;

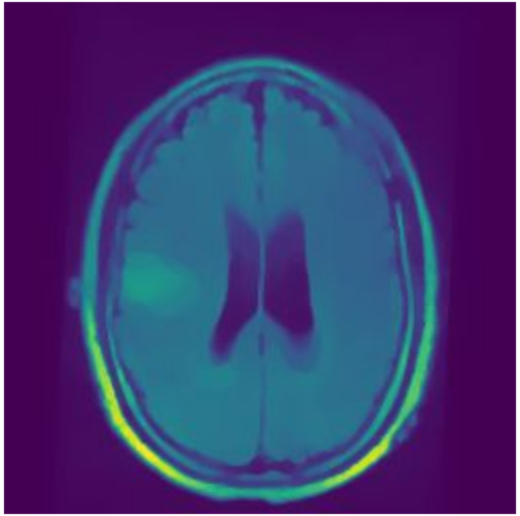
Slide 7: U-net: Convolutional networks for biomedical image segmentation;

Slide 9: https://www.kaggle.com/mateuszbuda/lgg-mri-segmentation

Appendix

Denoised images with Total Variation Algorithm





Denoised images with Total Variation Algorithm