



From Neonatal to Adult Brain MR Image Segmentation in a Few Seconds Using “3D-Like” Fully Convolutional Network and Transfer Learning

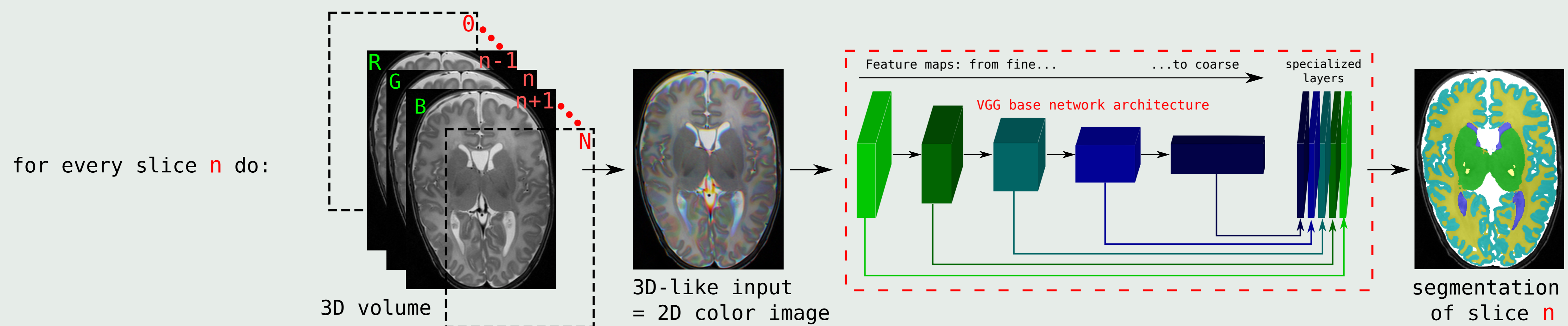


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At a glance



Problem:

- We want a precise segmentation of MRI brain volumes...
- ...and we want it quick.

Why our approach is interesting:

- it is simple, light, and versatile

Conclusion:

- a new approach to handle 3D volumes with CNN
→ the “3D-like” approach
- transfer learning works for medical image segmentation
- state-of-the-art results... obtained in a few seconds

Most important stuff

What people do:

- 3D patches at every voxel [5]
- 2,5D patches = 3 2D patches at every voxel [6]
→ that is heavy / slow
- a dedicated network [...]
→ a large dataset for training is required

What we propose:

- input a FCNN network with a series of 2D images
→ 3 slices of a volume = 1 2D color image
≈ **3D-like**
- reuse a fast and pre-trained base network (VGG [1])
→ transfer learning [4]

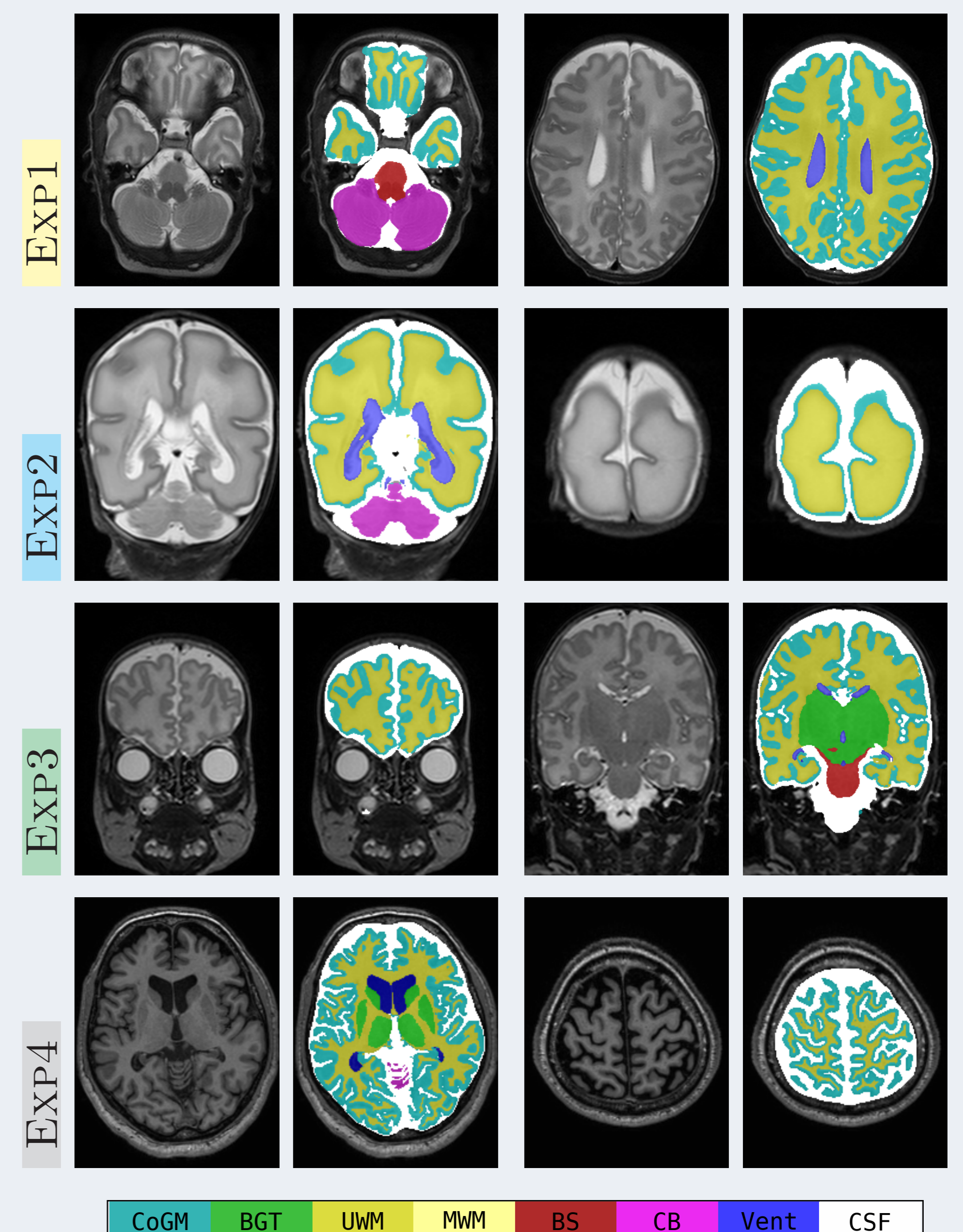
Training + test datasets [2, 3]

Dataset	Image set	# voxels	Size (mm ³)	Experiment (# images)	Code
NeoBrain12	Axial / 40 weeks	512×512×50	0.35×0.35×2.0	2 training / 5 test T2	EXP1
	Coronal / 30 weeks	384×384×50	0.34×0.34×2.0	2 training / 5 test T2	EXP2
	Coronal / 40 weeks	512×512×110	0.35×0.35×1.2	2+2 training / 5 test T2	EXP3
MRBrainS13	Axial / 70 years	240×240×48	0.96×0.96×3.0	5 training / 15 test T1	EXP4

Quantitative results

Code	Method	CoGM		BGT		UWM		BS		CB		Vent		CSF		Timing
		DC	MSD	DC	MSD	DC	MSD	DC	MSD	DC	MSD	DC	MSD	DC	MSD	
EXP1	Our	0.87	0.11	0.91	0.51	0.93	0.11	0.85	0.49	0.94	0.33	0.87	0.24	0.83	0.20	3.5 s
	UPF_SIMBioSys	0.85	0.15	0.93	0.29	0.91	0.17	0.85	0.15	0.94	0.28	0.83	0.44	0.79	0.29	
	UNC-IDEA	0.86	0.11	0.92	0.33	0.92	0.13	0.83	0.27	0.92	0.45	0.79	0.25	0.79	0.25	
	5 next (median)	0.84	0.18	0.88	0.62	0.88	0.25	0.79	0.69	0.91	0.53	0.81	0.32	0.73	0.54	
EXP2	Our	0.79	0.14	0.89	0.42	0.95	0.14	0.84	0.37	0.91	0.30	0.87	0.33	0.89	0.13	2.2 s
	UPF_SIMBioSys	0.75	0.16	0.90	0.38	0.93	0.22	0.86	0.32	0.92	0.31	0.88	0.25	0.85	0.17	
	CIMAT_Team	0.69	0.26	0.89	0.41	0.93	0.28	-	-	-	-	0.82	0.22	0.82	0.22	
	5 next (median)	0.60	0.38	0.82	0.77	0.87	0.46	0.71	0.88	0.87	0.40	0.86	0.41	0.74	0.46	
EXP3	Our	0.79	0.21	0.86	0.98	0.91	0.18	0.68	1.13	0.89	0.65	0.82	0.41	0.82	0.30	6.5 s
	MorphoSeg	0.77	0.21	0.86	0.96	0.89	0.24	0.72	0.95	0.91	0.55	0.78	0.39	0.78	0.39	
	UPF_SIMBioSys	0.73	0.27	0.89	0.52	0.87	0.30	0.76	0.53	0.91	0.59	0.85	0.34	0.72	0.55	
	5 next (median)	0.72	0.28	0.87	0.87	0.85	0.35	0.73	0.84	0.91	0.62	0.81	0.48	0.71	0.59	
EXP4	Our	0.86	1.44			0.89	1.86							0.82	2.28	1.7 s
	CU_DL	0.86	1.47			0.89	1.94							0.83	2.28	
	MDGRU	0.85	1.55			0.88	2.02							0.84	2.17	
	7 next (median)	0.84	1.67			0.88	2.07							0.82	2.30	

Some qualitative results



Selected bibliography

- [1] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” *CoRR*, vol. abs/1409.1556, 2014.
- [2] I. Išgum *et al.*, “Evaluation of Automatic Neonatal Brain Segmentation Algorithms: the NeoBrainS12 Challenge,” *Medical Image Analysis*, vol. 20, no. 1, pp. 135-151, 2015.
- [3] A. M. Mendrik *et al.*, “MRBrainS challenge: Online evaluation framework for brain image segmentation in 3T MRI scans,” *Computational Intelligence and Neuroscience*, 2015.
- [4] J. Long, E. Shelhamer, and T. Darrell, “Fully convolutional networks for semantic segmentation,” in *CVPR*, 2015, pp. 3431-3440.
- [5] H. Chen *et al.*, “VoxResNet : Deep voxelwise residual networks for volumetric brain segmentation,” <https://arxiv.org/abs/1608.05895>, 2016.
- [6] K. Fritscher *et al.*, “Deep neural networks for fast segmentation of 3D medical images,” in *MICCAI*, vol. 2, 2016, pp. 158-165.

Supplementary materials: <http://publications.lrde.epita.fr/xu.17.icip>