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M-net: A Convolutional Neural Network for Deep Brain Structure Segmentation

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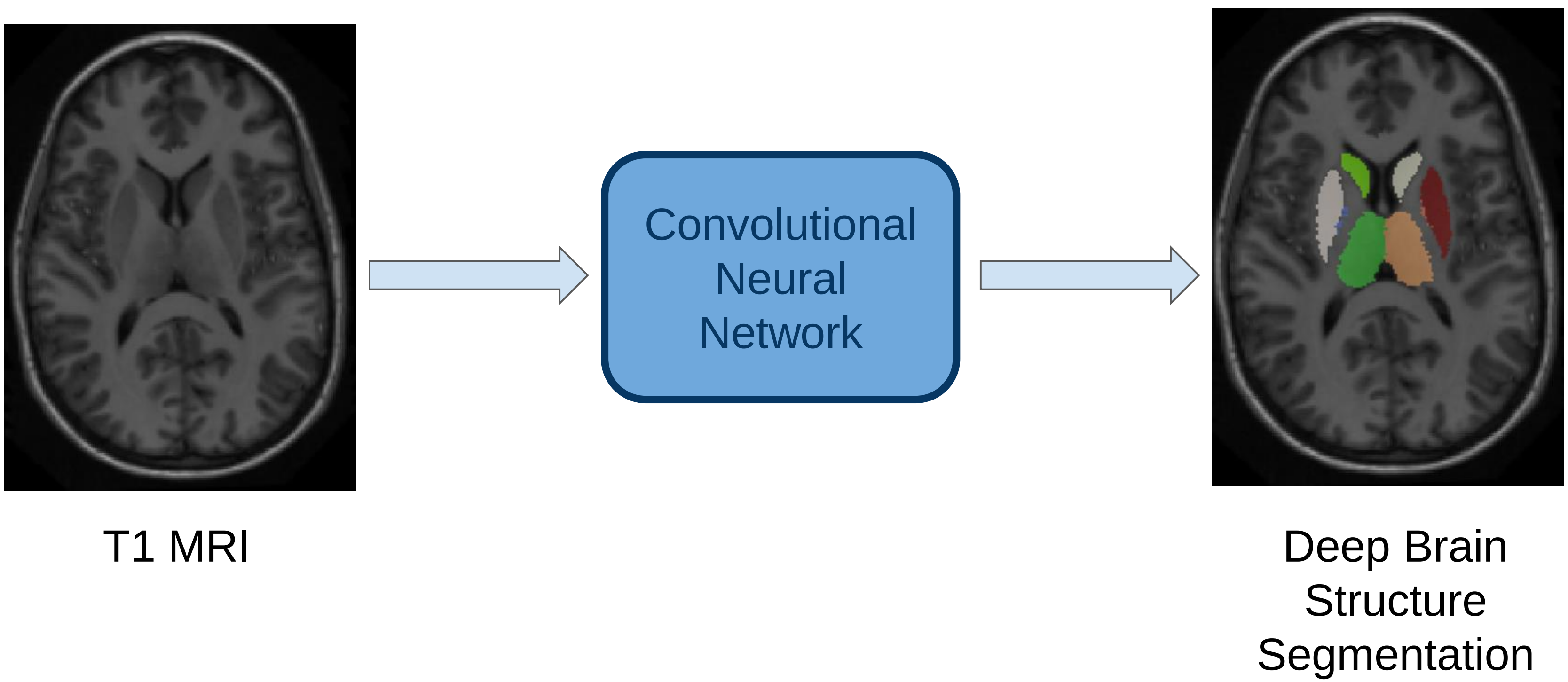
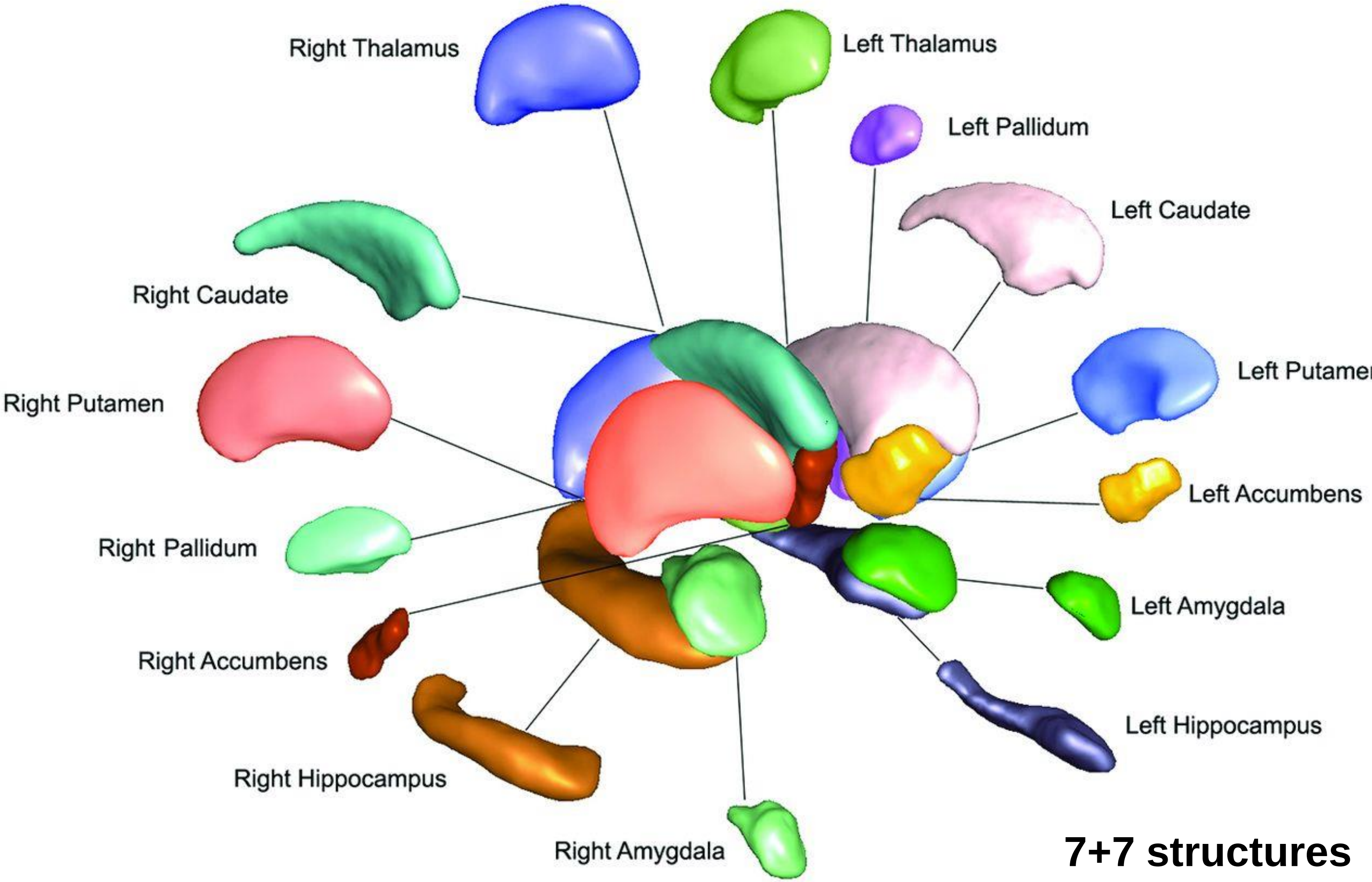
Segmentation problem



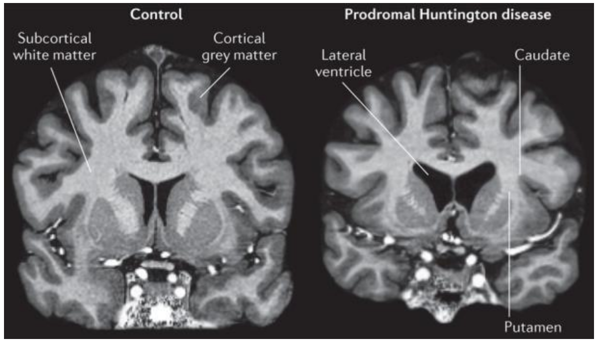
Deep Brain Structures



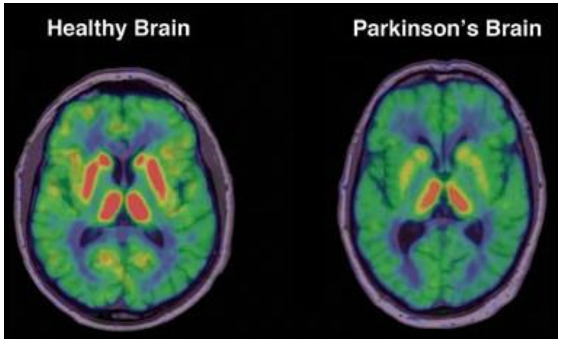
7+7 structures

Motivation

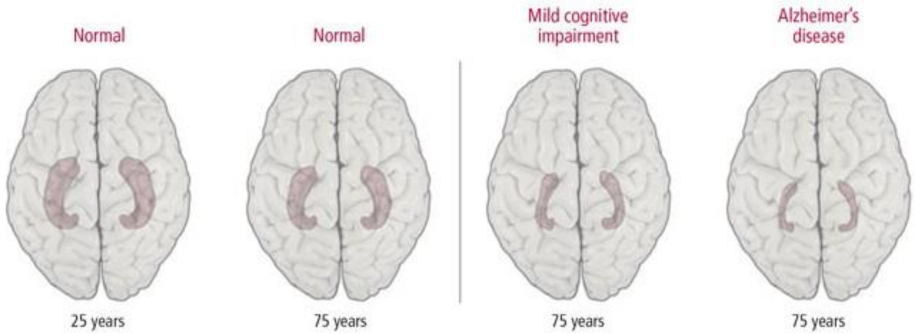
Morphometry of deep brain structures is an *important biomarker* for various neurodegenerative diseases.



Huntington Disease
(Basal Ganglia)



Parkinson's Disease
(Putamen)



Alzheimer's Disease
(Hippocampus)

Related Work [1]

Registration based methods [2]	Model based methods [3,4]
• Non-rigid registration of training *atlases* to the new volume • Followed by label Fusion • Time intensive (20-25 hours) • Unsuitable for applications which are time critical	• Learn a mathematical model using *atlases* (during training) • Segment the new volume using the learnt model • Efficient (15-20 minutes) • Suitable for applications which are time critical

(1) Iglesias et al., MedIA 2015 (Review Paper)
(2) Heckemann et al., NeuroImage 2006
(3) Patenaude et al., NeuroImage 2011 (FSL-FIRST)
(4) Fischl et al, Neuron 2002 (Freesurfer)

Machine Learning based Methods

Pose segmentation as a classification task:

Random Forest + Markov Random Field [1]

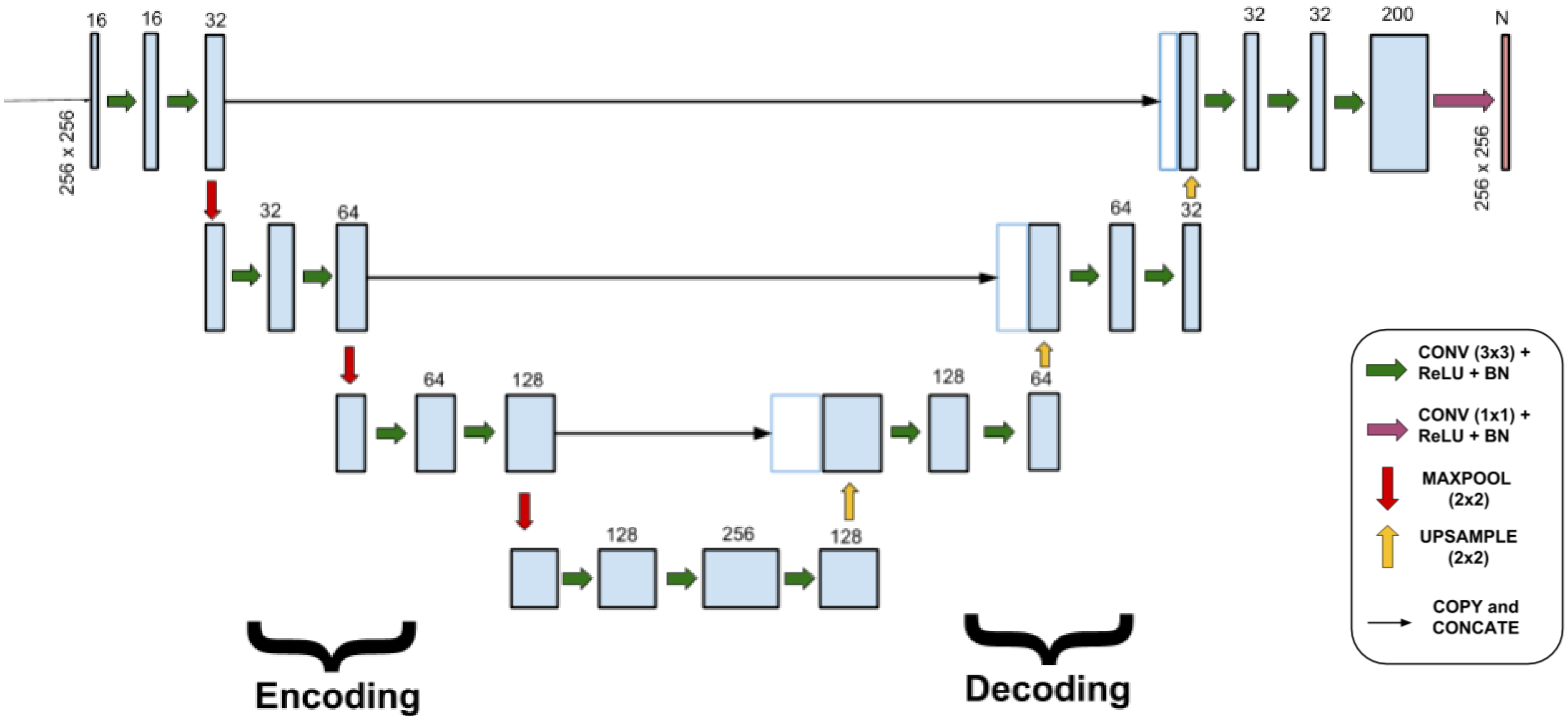
Multi Scale - CNN + Random Walker [2]

Fully Convolutional NN + Markov Random Field [3]

(1) Alchatzidis et al. BMVC 2014
(2) Bao et al., CMBBEIV 2016
(3) Shakeri et al., ISBI 2016

Inspiration

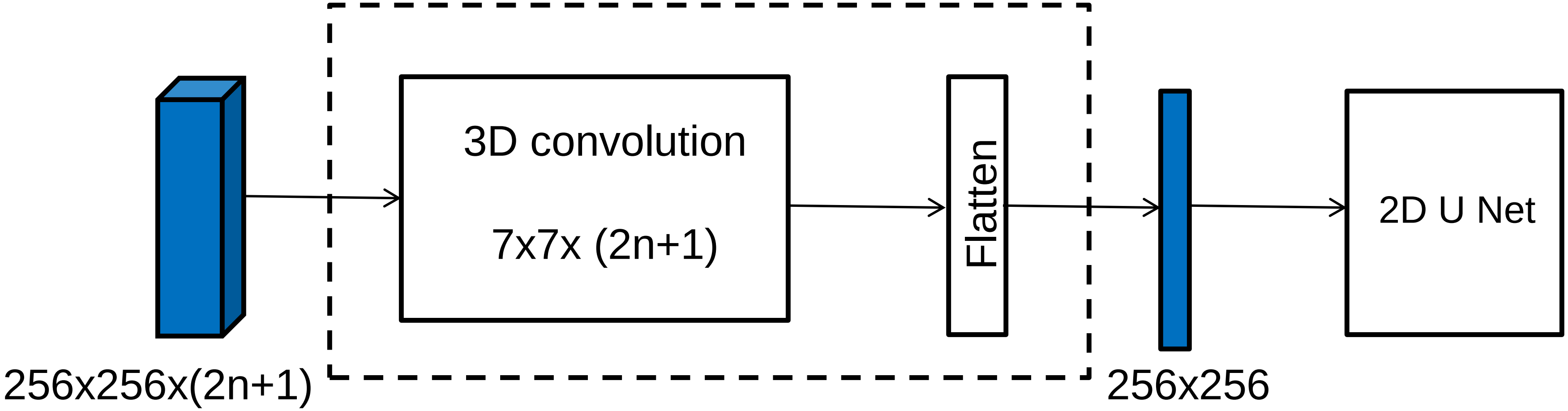
U-Net [1,2] - Proposed for microscopy



(1) Olaf Ronneberger et al.,MICCAI-2015 (2D)
(2) Ozgun Cicek et al., MICCAI-2016 (3D)

Proposal 1: modified input stage

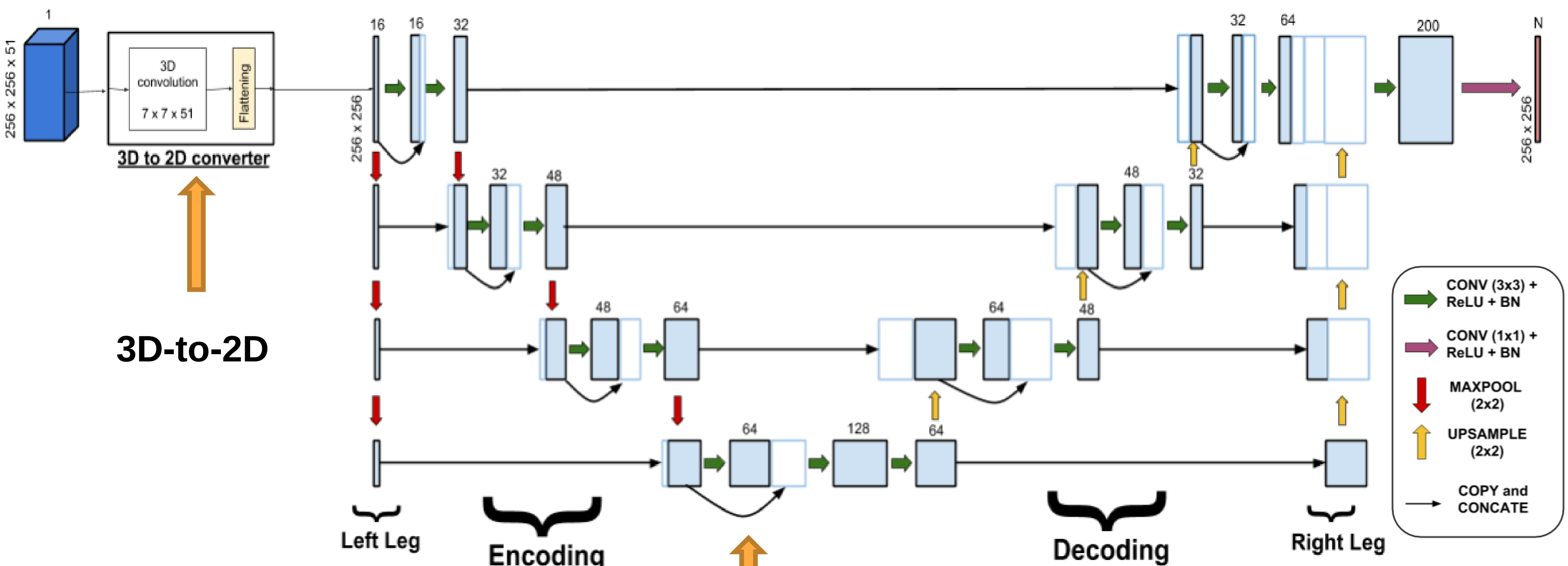
Add a 3D-to-2D converter as a front end



This is to ensure label consistency

Proposal 2 - more modifications

Final solution: The M-net



3D-to-2D

Skip connections

Original intensity at multiple scales

Supervision

Experiments

Datasets:

- Internet Brain Segmentation Repository (IBSR)
- 18 volumes; 256x256x12; 1x1x1.5 mm^3

- MICCAI-2013 SATA Diencephalon Challenge (Mid-brain) – Open competition
- 35 training + 12 testing volumes; 256x256x300; 1x1x1 mm^3

- Annotations for 7 subcortical (left/right) structures:

  Accumbens Area, Amygdala, Pallidum, Caudate, Hippocampus

  Putamen and Thalamus

Implementation

- CNN trained on K40 GPU with 12 GB of RAM
- Training time ~ 3 days
- Code in Python with Keras library [1]
- Optimizer: Adam [2]
- Hyper parameters: LR = 0.001, $\boldsymbol{\beta}_1 = 0.9$, $\boldsymbol{\beta}_2 = 0.999$ and $\boldsymbol{\epsilon} = 10^{-08}$
- Number of neighbor slices (n): 25

❑ Evaluation

$$DC(A,B) = \frac{2|AB|}{|A| + |B|}$$

(1) Fran Chollet, 2015 (https://github.com/fchollet/keras)
(2) KIngma et al.,arXiv - 2014

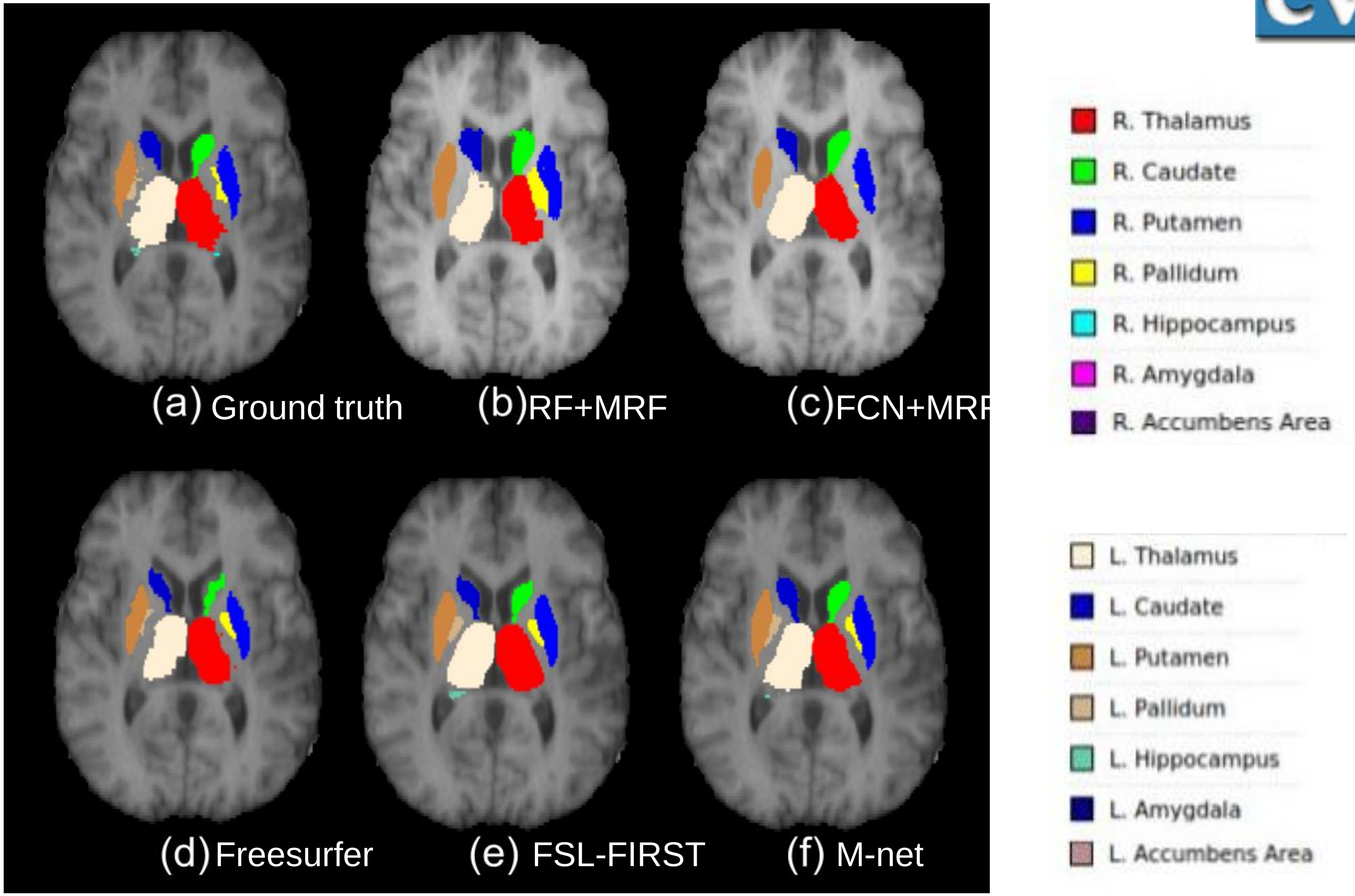
Results on IBSR

Mean Dice coefficient

	Freesurfer[1] Tool	FSL [2] Tool	RF + MRF [3]	FCN + MRF [4]	MS-CNN+MRF [5]	U-net + 3D-to-2D Conv	M-net
Accumbens	0.69	0.73	0.60	0.63	0.69	0.71	**0.75**
Amygdala	0.69	0.70	0.62	0.64	0.67	0.70	**0.73**
Pallidum	0.71	0.76	0.62	0.75	0.80	0.80	**0.82**
Caudate	0.82	0.83	0.78	0.78	**0.87**	0.85	**0.87**
Hippocampus	0.77	0.81	0.59	0.71	**0.82**	0.81	**0.82**
Putamen	0.81	0.84	0.77	0.83	0.88	0.89	**0.90**
Thalamus	0.86	0.88	0.80	0.87	**0.90**	0.88	**0.90**
Overall	0.76	0.79	0.69	0.75	0.80	0.81	**0.83**

(1) Fischl et al., Neuron 2002
(2) Patenaude et al., NeuroImage 2011
(3) Alchatzidis et al., BMVC 2014
(4) Shakeri et al., ISBI 2016
(5) Bao et al., CMBBEIV 2016

Results on IBSR

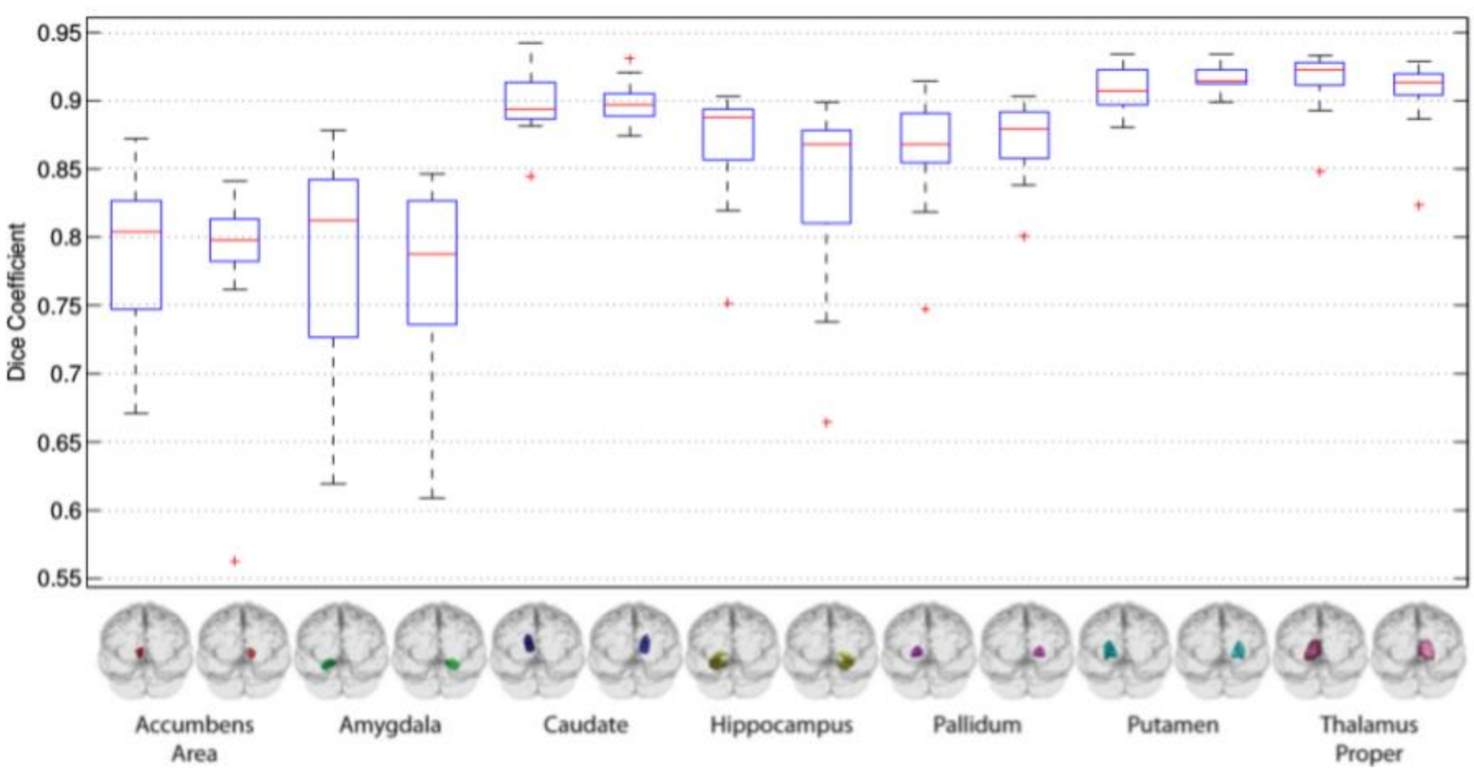


Results on SATA Diencephalon

Mean Dice coefficient

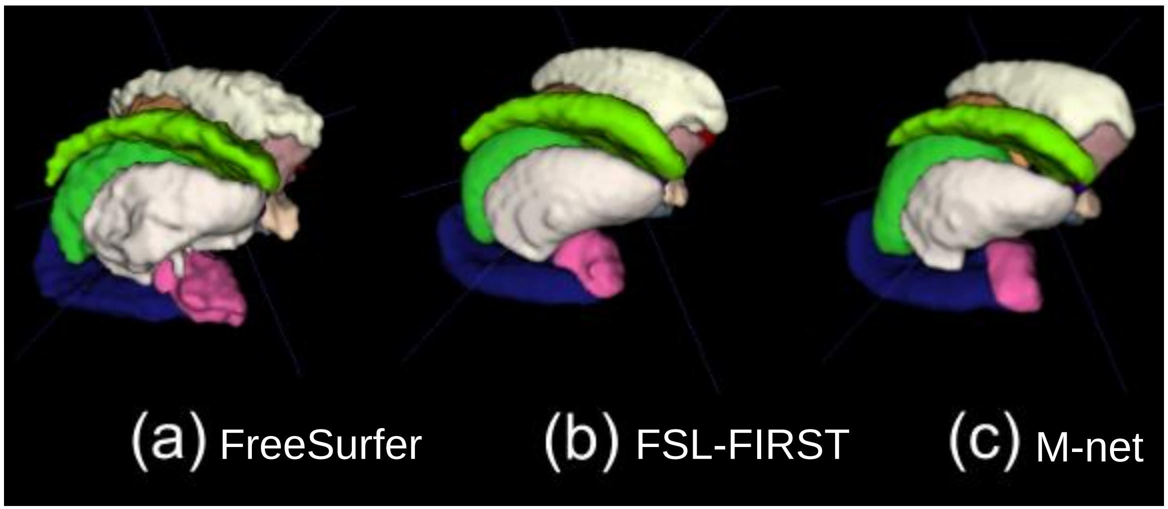
FSL-FIRST : 0.82437 Freesurfer : 0.75761

Atlas-Forest [1] : 0.82819 **M-net : 0.85780**



(1) Zikic et al. MedIA, *2014*.

Results: SATA Diencephalon



- R. Accumbens Area
- L. Accumbens Area
- R. Amygdala
- L. Amygdala
- R. Caudate
- L. Caudate
- R. Hippocampus
- L. Hippocampus
- R. Pallidum
- L. Pallidum
- R. Putamen
- L. Putamen
- R. Thalamus
- L. Thalamus

Summary

Proposed M-net

- Labels 3D MRI volumes *slice by slice*
- Label consistency and low memory requirement
- Computationally efficient (~5 min on *standard CPU*)
- No need for post-processing

- M-net can be used for segmentation of *any* 3D dataset

Thank You!

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Whole Brain Segmentation

MICCAI 2012 Multi-Atlas Labeling Challenge [1]

- 15 Training Volumes, 20 Testing Volumes
- Segmentation into 134 structures
  - 98 cortical
  - 36 non-cortical

Mean Dice coefficient

U-net 2D	:	0.6624
U-net + 3D-to-2D conv	:	0.6971
M-net	:	0.7278

(1) Landman, B., Warfield, S. (Eds.), 2012. MICCAI 2012 Workshop on Multi-Atlas Labeling.

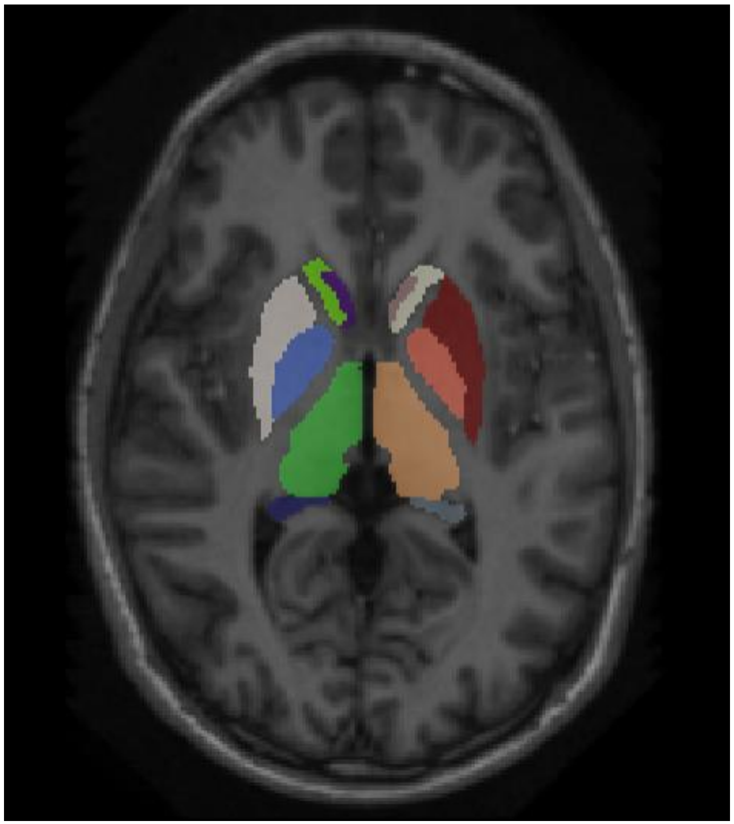
Comparison with 3D network

Mean Dice Coefficient on IBSR dataset

	M-net	3D FCNN [1]
Pallidum	0.82	0.86
Caudate	0.87	0.91
Putamen	0.90	0.90
Thalamus	0.90	0.92

(1) Dolz, J., Desrosiers, C. and Ayed, I.B., **2016**. 3D fully convolutional networks for subcortical segmentation in MRI: A large-scale study. *arXiv preprint arXiv:1612.03925*.

Deep Brain Structures



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