MAIA

Brain Tissue Segmentation Using NeuroNet With Different Pre-processing Techniques

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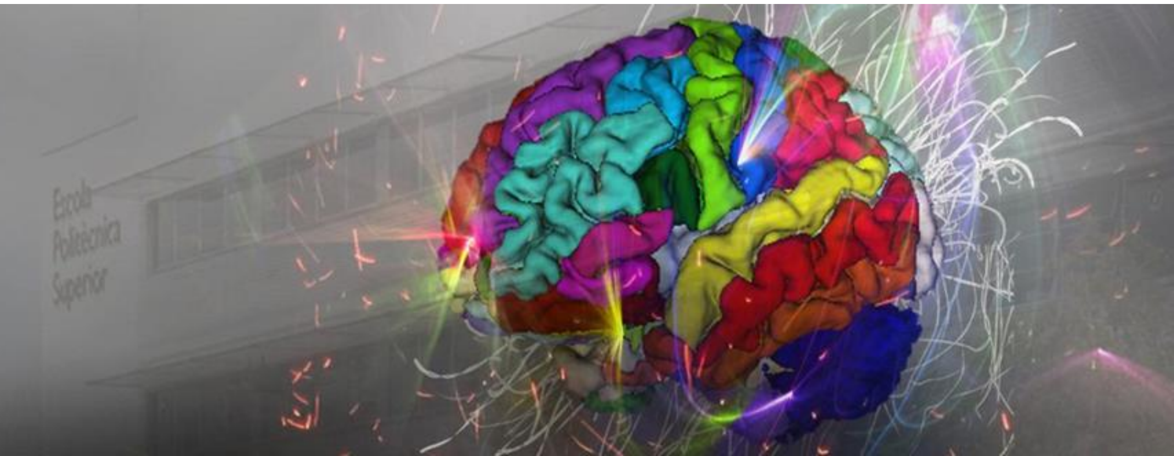

Outline

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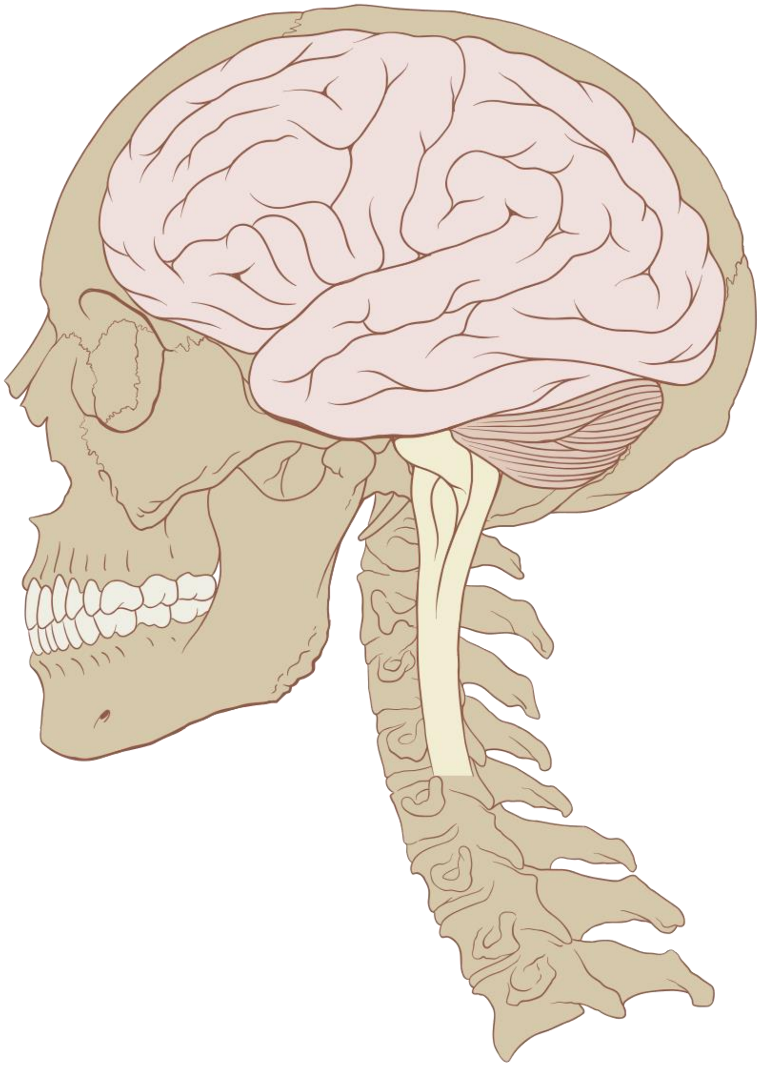
1. Introduction

- Neurological disorders ranked as the second-leading cause group of deaths (9·4 million) comprising **16·8%** of global deaths.



Feigin, V. L., et al. (2017). "Global, regional, and national burden of neurological disorders during 1990–2015: a systematic analysis for the Global Burden of Disease Study 2015."
The Lancet Neurology **16**(11): 877-897.

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1. Introduction: CAD

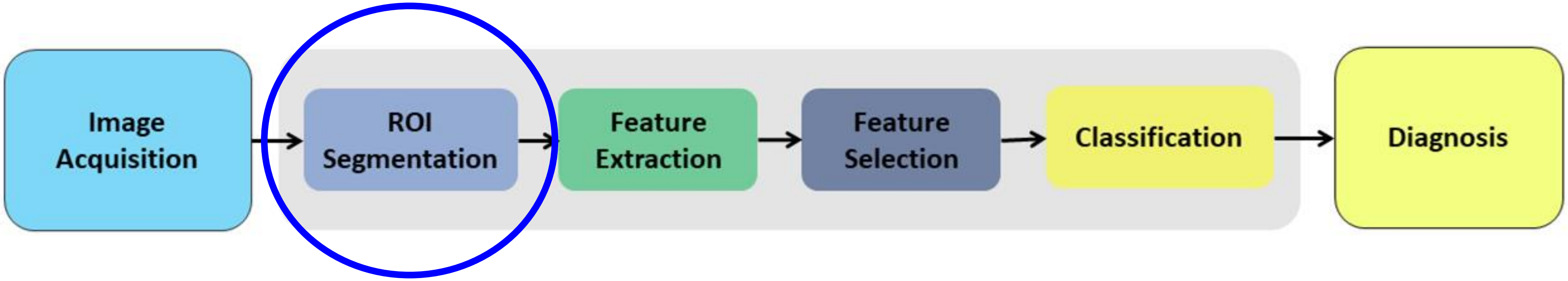

Fig-1. Generalized block diagram of computer-aided diagnosis (CAD) systems.

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1.Introduction:Magnetic Resonance Imaging

Magnetic Resonance Imaging (MRI)

- Widely used in medical practice
- A standard tool for: diagnosis, disease follow-up, evaluation.
- Provides good contrast between tissues

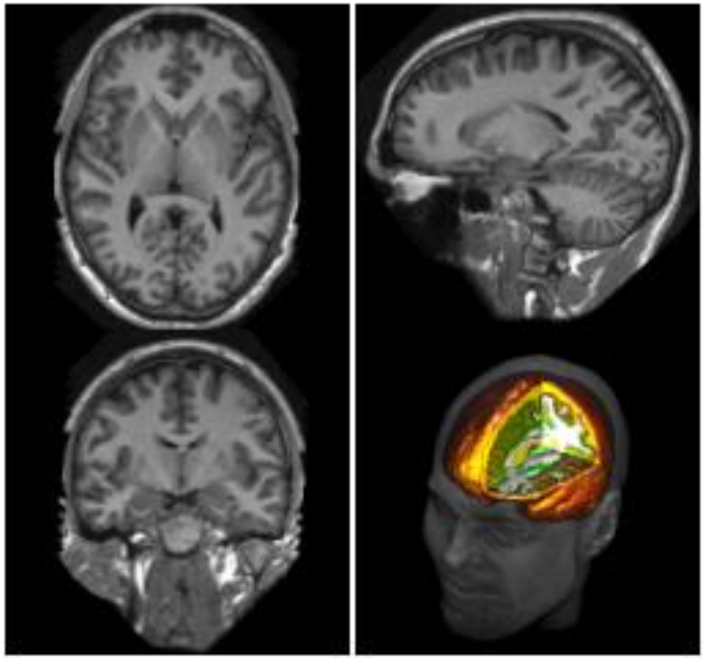

Fig-2.T1 weighted MR image example.

1.Introduction: Brain Tissue Segmentation

- Classify each voxel in an input 3D volume into Grey Matter (GM), White Matter (WM) or CerebroSpinal Fluid (CSF).

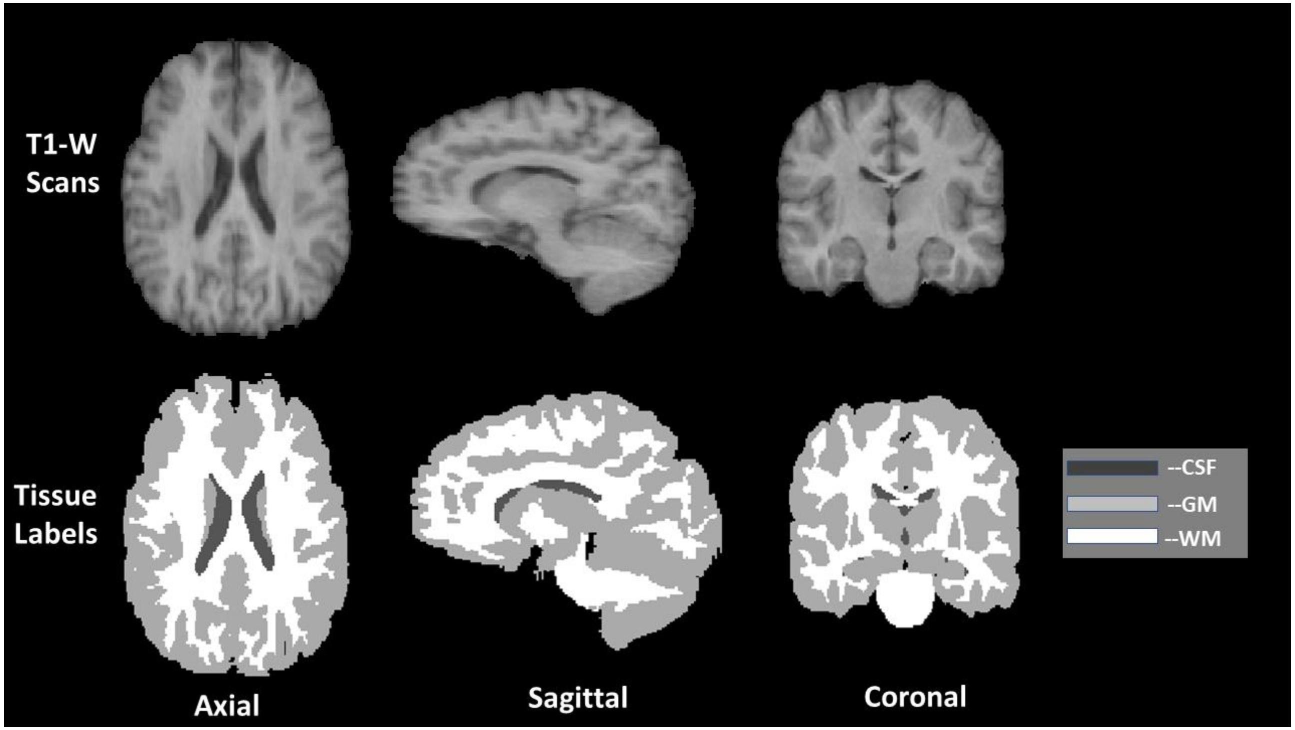

Fig-3. Graphical representation of a volume and corresponding tissue labels in axial, sagittal and coronal view.

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2. Dataset

- IBSR-18 Dataset, 18 MR volumes T1 weighted.

Table-1: Summary of IBSR18 dataset used in this paper.

Volume Name	Volume	Spacing (mm)
Training Subset		
IBSR 01, 03, 04, 06	$256 \times 128 \times 256$	$0.94 \times 1.5 \times 0.94$
IBSR 07,08,09	$256 \times 128 \times 256$	$1 \times 1.5 \times 1$
IBSR 16,18	$256 \times 128 \times 256$	$0.84 \times 1.5 \times 0.84$
Validation Subset		
IBSR 11, 12	$256 \times 128 \times 256$	$1 \times 1.5 \times 1$
IBSR 13,14	$256 \times 128 \times 256$	$0.94 \times 1.5 \times 0.94$
IBSR 17	$256 \times 128 \times 256$	$0.84 \times 1.5 \times 0.84$
Test Subset		
IBSR 02	$256 \times 128 \times 256$	$0.94 \times 1.5 \times 0.9375$
IBSR 10	$256 \times 128 \times 256$	$1 \times 1.5 \times 1$
IBSR 15	$256 \times 128 \times 256$	$0.84 \times 1.5 \times 0.84$

IBSR-18 Dataset. Available at: https://www.nitrc.org/frs/?group_id=48.
Accessed: 2019-01-05.

3. Previous Studies

Traditional brain tissue segmentation approaches:

- Region-based.
- Clustering-based.
- Statistical based methods.
- Classification methods based on Feature engineering.

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4. Method: DCNN

- DNCC Becomes obvious choice to the Computer vision societies

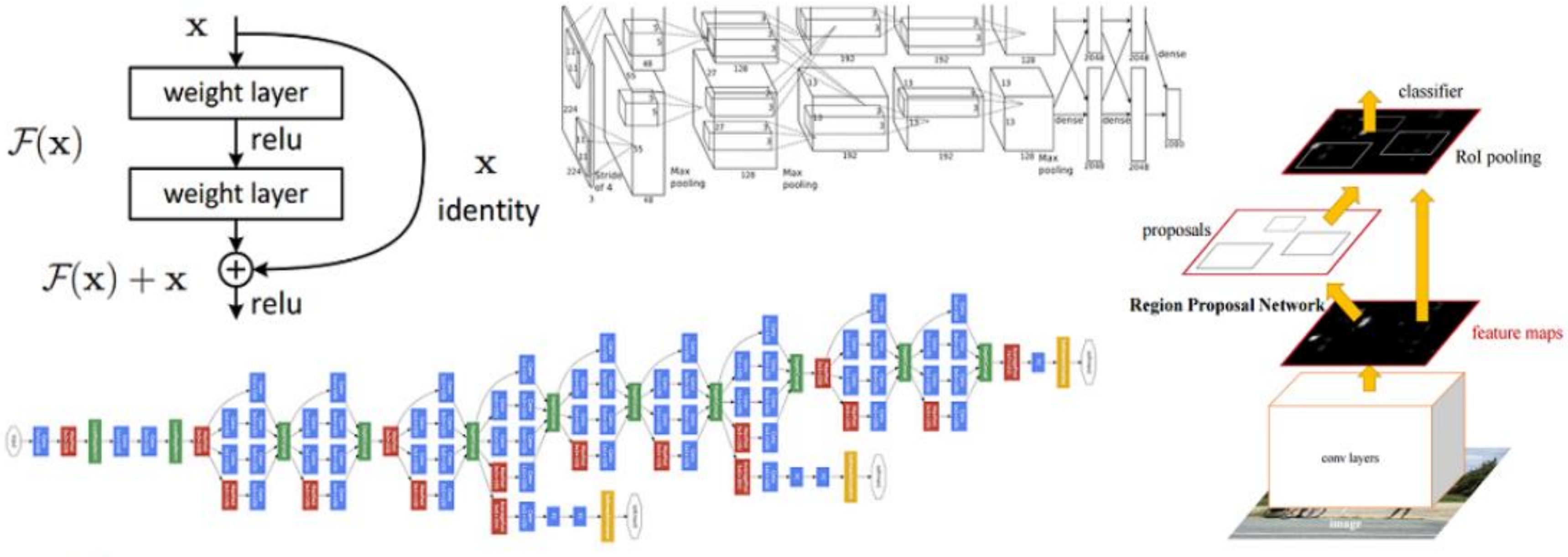

Fig-4. Examples of state-of-the-art CNN architectures.

4. Method: DCNN

- Limitation of DCNN for Medical Imaging ?

✔ **Having huge amount of data is challenging for Medical Cases**

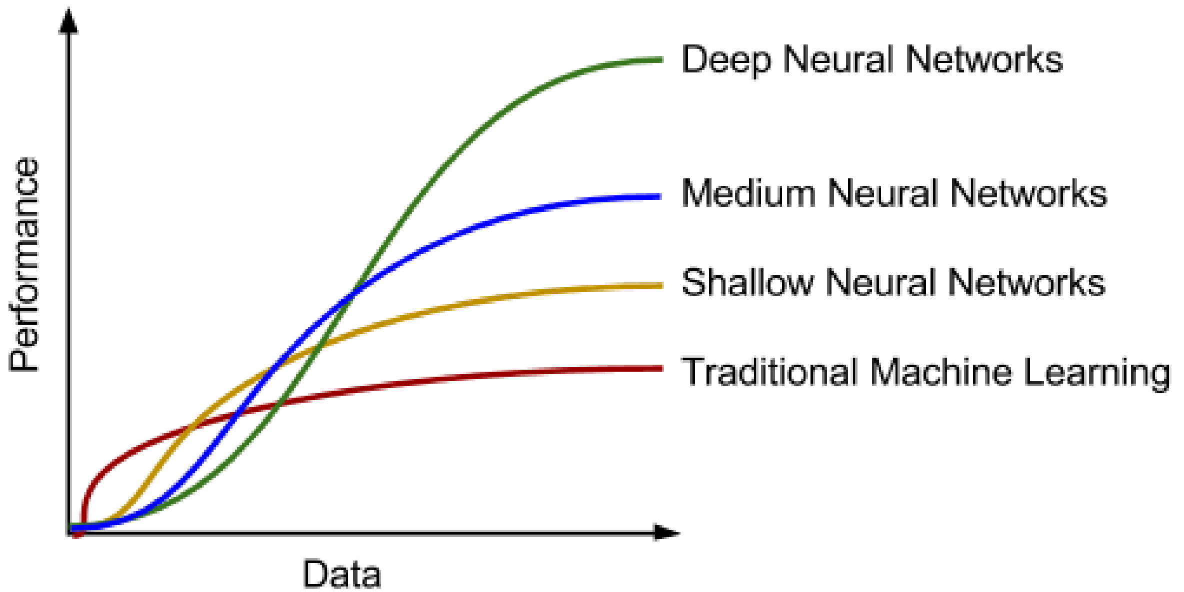

Fig-5. Graph illustrating the impact of data available on performance.

Tang, A., et al. (2018). "Canadian Association of Radiologists White Paper on Artificial Intelligence in Radiology." Can Assoc Radiol J **69**(2): 120-135.

4. Method: Transfer Learning

- **Transfer Learning**
- Using a pretrained model and Fine tune it according to need

- Fine Tuning Approach:

✓ **Use as Fixed Feature Extractor**

✓ **Replace the last layer with a new classifier**

✓ **Train the last Convolutional layer only and freeze others**

✓ **Partially trained the model**

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4. Method: NeuroNet

Used CNN architecture:

- Resolution scale: 4
- Filter: 16,32,64,126.
- Down-sampled by Stride Convolution
- Linear up-sampled and skip connections
- prediction obtained after a softmax layer.

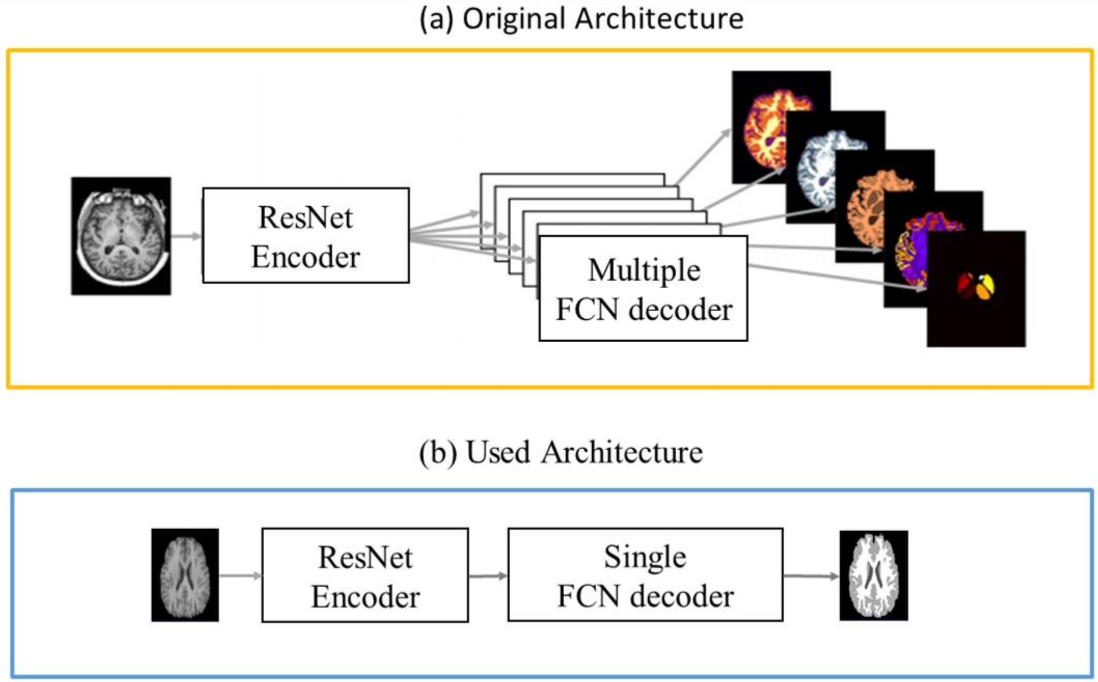

Fig-6. Original and Used NeuroNet Architecture.

M. Rajchl, (2018). NeuroNet: Fast and Robust Reproduction of Multiple Brain ImageSegmentation Pipelines. *arXiv e-prints*.

4. Method: Pre-processing Pipelines

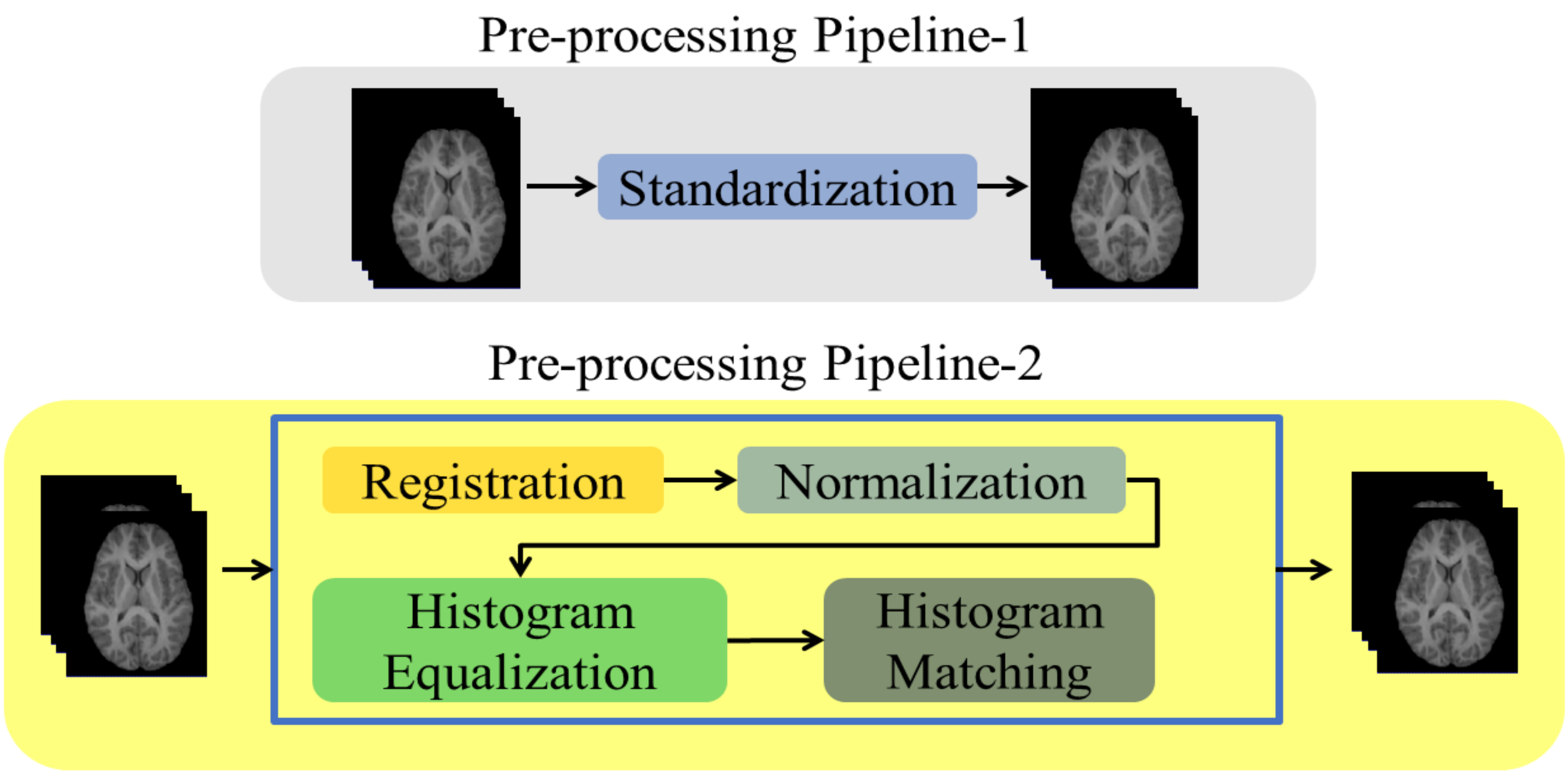

Fig-7: Proposed pre-processing pipelines.

4. Method: Pre-processing pipeline-2

- Registration to MNI template.

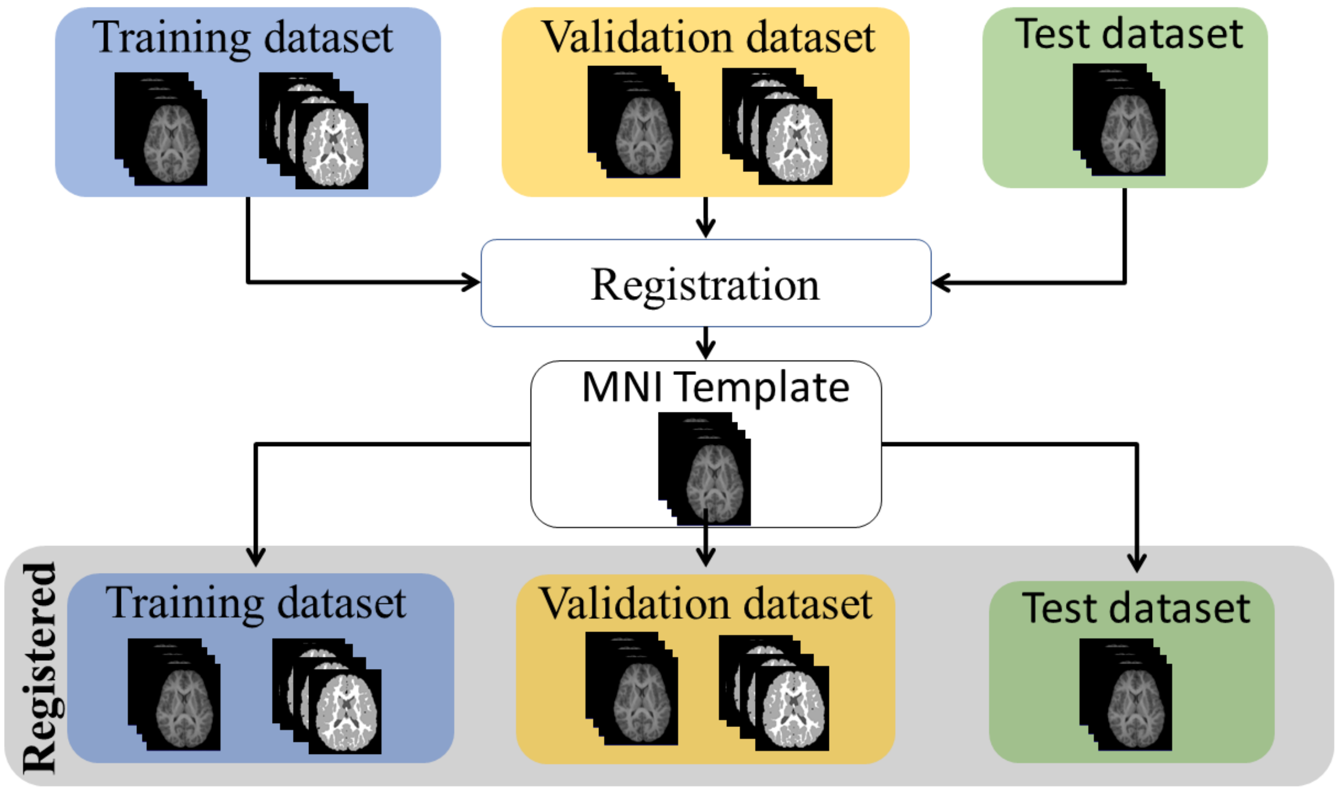

Fig-8: Registering the whole dataset to MNI template to unify the voxel spacing.

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4. Method: Pre-processing pipeline-2

- Intensity distributions

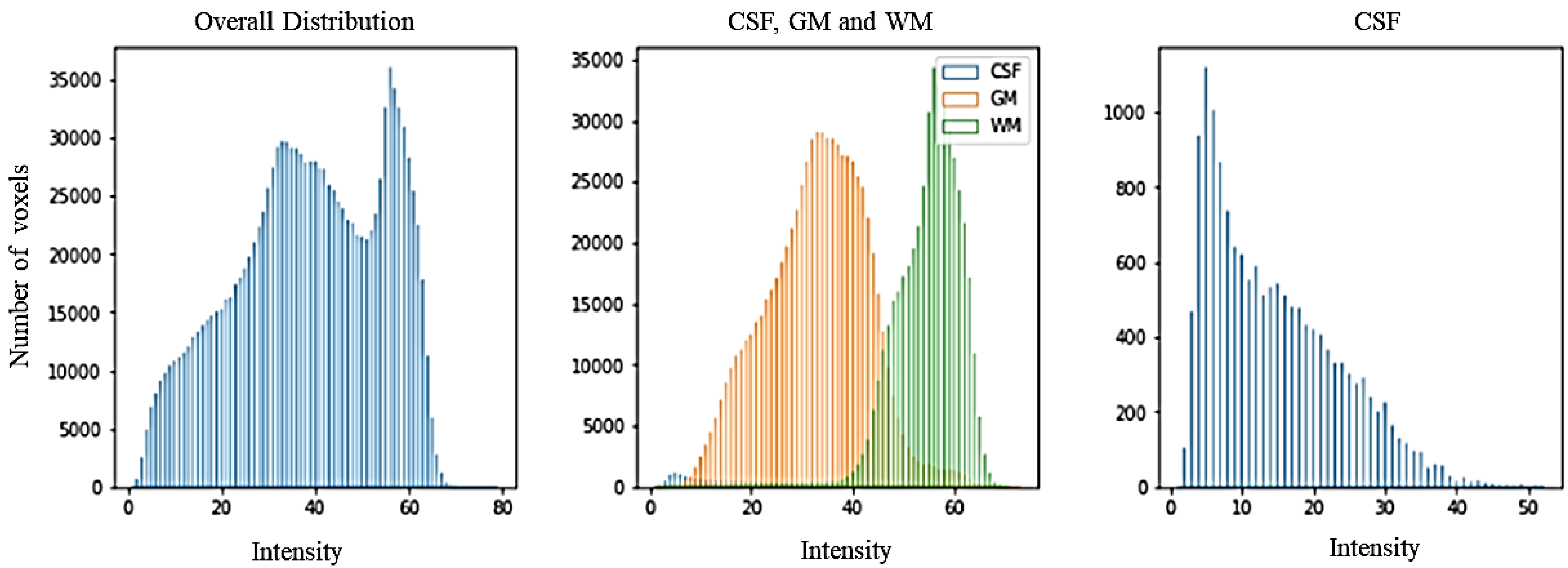

Fig-9: IBSR 07 intensity distributions, where, on the left, the complete tissues intensity distribution, while, in the middle, CSF, WM and GM distributions with different colors. The figure on the right is for CSF distribution only.

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4. Method: Pre-processing pipeline-2

Histogram pre-processing:

- Reference Selection
- Histogram Equalization of Reference Volume
- Histogram Matching to the Reference One

4. Methods: Pre-processing pipeline-2

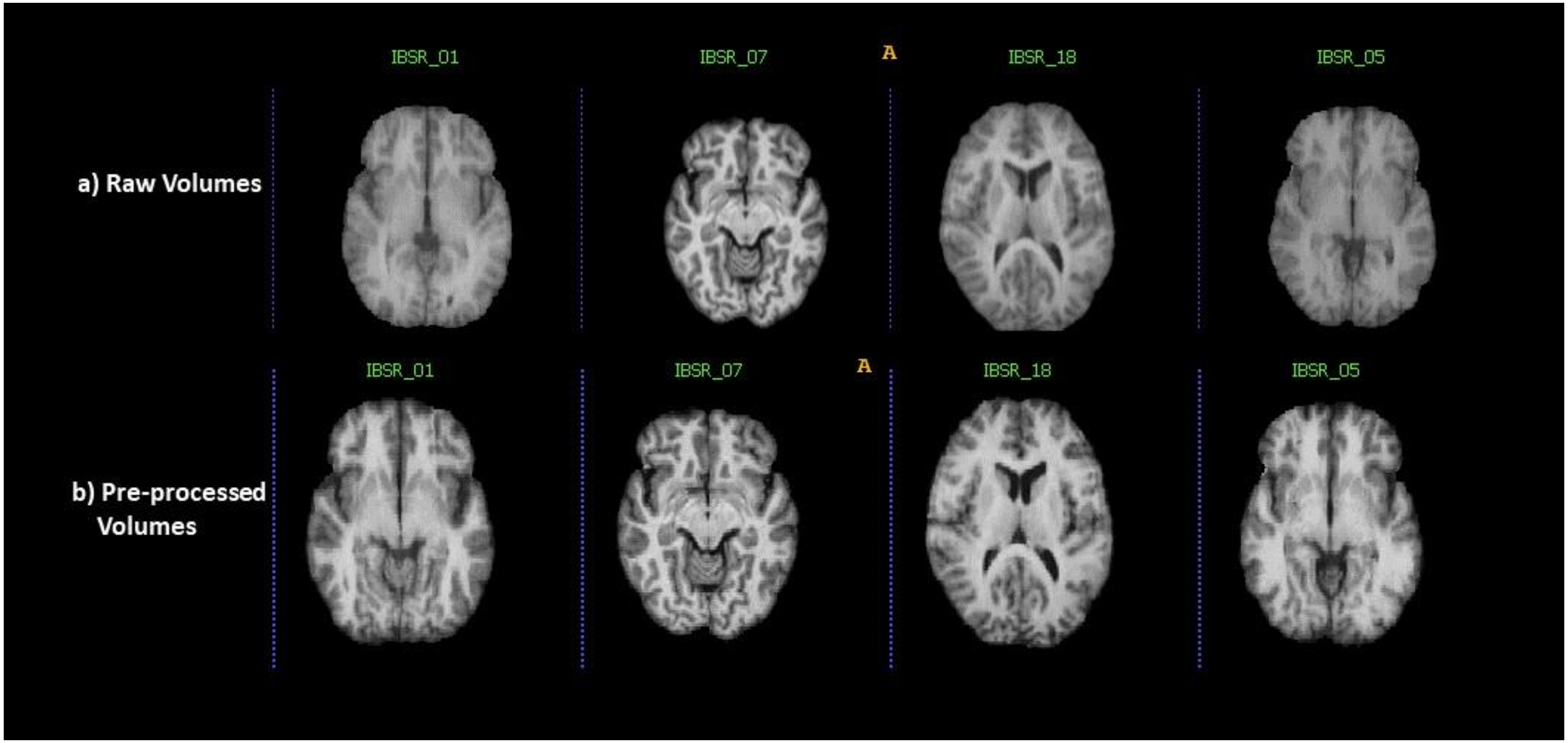
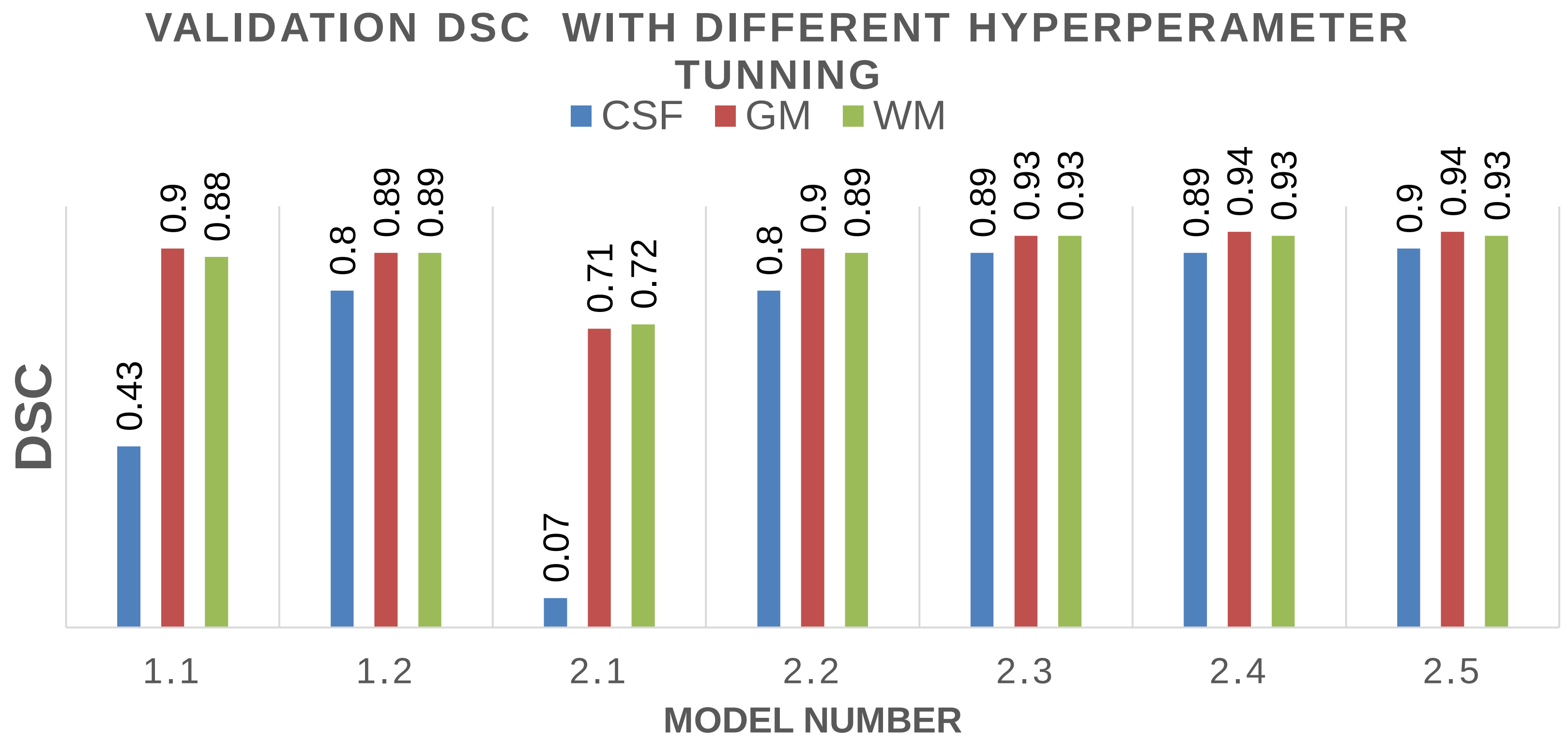


Fig-10: The effect of pre-processing. At the top, 4 cases before applying the pre-processing pipelines. At the bottom, the final pre-processed dataset

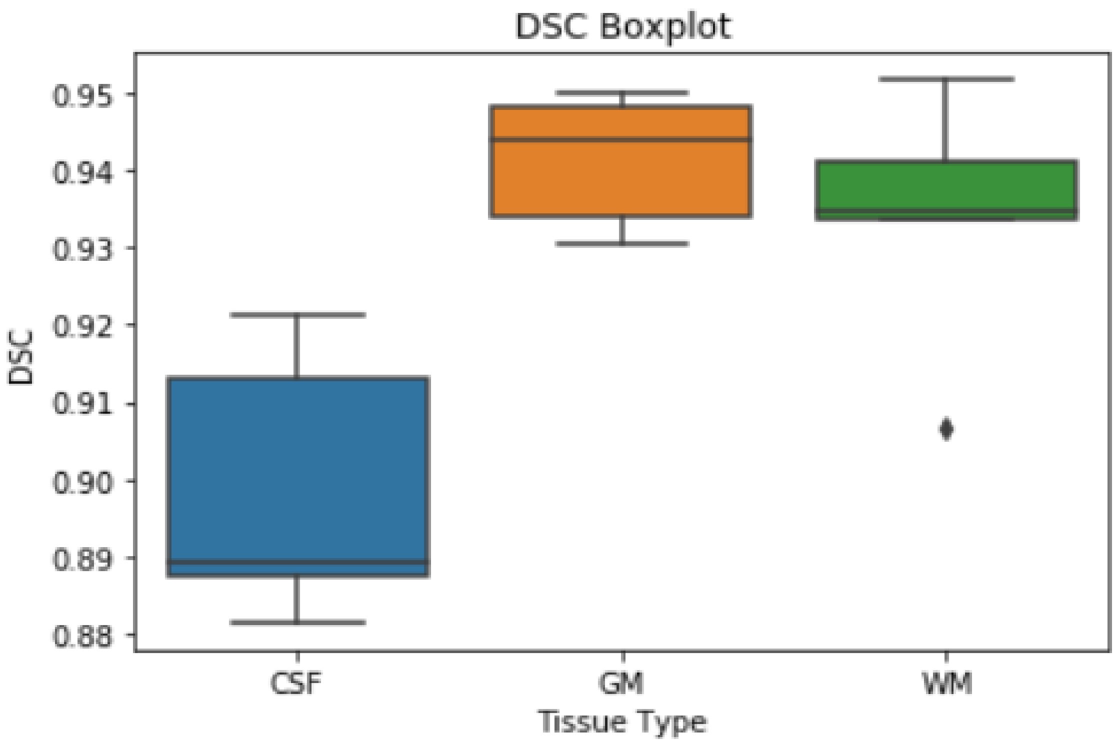
5. Experiments and Results



Model Configuration					Dice Coefficient Validation Set		
Model No.	#Training Steps	Patch Size	Samples	Weights Initializations	CSF	GM	WM
1.1	1000	128x128x128	200	NeuroNet Pretrained	0.43±0.40	0.90±0.01	0.88±0.06
1.2	5000	128x128x128	400	NeuroNet Pretrained	0.80±0.12	0.89±0.05	0.89±0.03
2.1	4000	32x32x32	200	Uniform Distribution	0.07±0.03	0.71±0.04	0.72±0.06
2.2	4000	64x64x64	200	Uniform Distribution	0.80±0.05	0.90±0.02	0.89±0.03
2.3	4000	128x128x128	50	Uniform Distribution	0.89±0.02	0.93±0.01	0.93±0.01
2.4	2000	128x128x128	50	NeuroNet Pretrained	0.89±0.02	0.94±0.01	0.93±0.01
2.5	**4000**	**128x128x128**	**50**	**NeuroNet Pretrained**	**0.90±0.02**	**0.94±0.01**	**0.93±0.02**

5. Experiments and Results

- **Test Results**



Average Test DSC:

- **CSF: 0.84**
- **GM: 0.94**
- **WM: 0.94**

6. Conclusion and Future work

- DL is better than traditional CV methods.
- Transfer learning is better choice with less images
- Preprocessing plays crucial roles.
- Future direction can be focused on improving generalization ability.

7. Resources

- **Codes and Trained weights:** https://github.com/fitushar/Brain-Tissue-Segmentation-Using-Deep-Learning-Pipeline-NeuroNet
- **Pre-print**: https://arxiv.org/abs/1904.00068
- **Email:** fakrulislam.tushar@duke.edu

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Thank You