Paper number: 230

Training deep segmentation networks on texture-encoded input: application to neuroimaging of the developing neonatal brain

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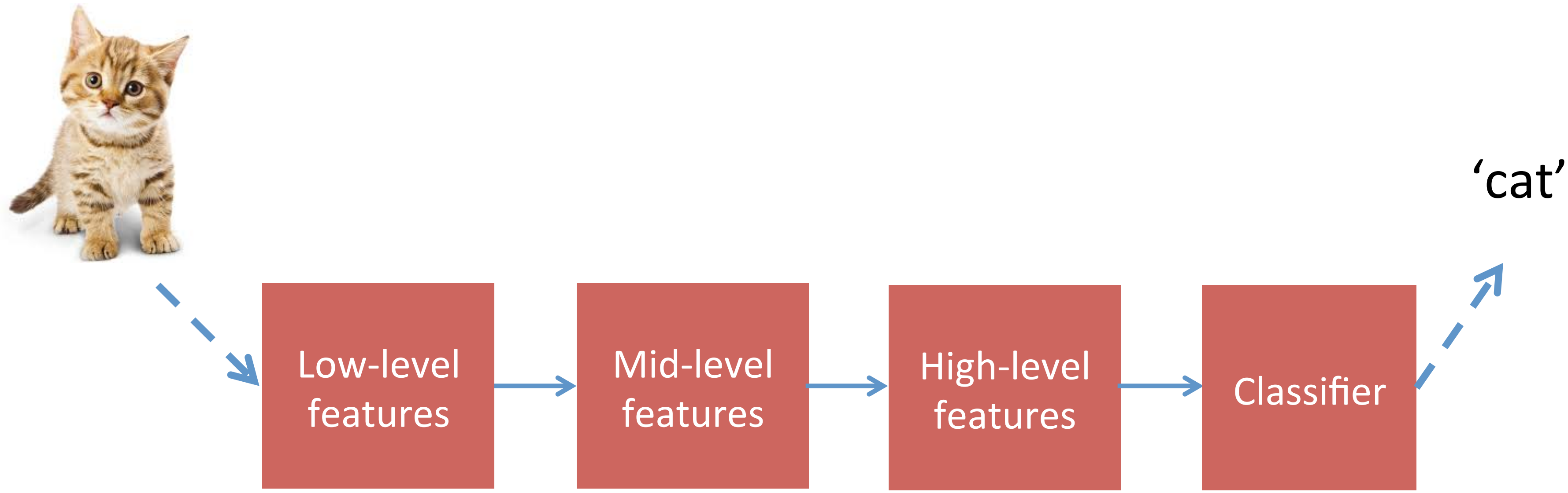
The ‘shape hypothesis’ in deep CNNs



e.g. lines, edges..

e.g. circles, triangles..

e.g. ears, paws..

Low level shape features are combined in increasingly complex hierarchies until the object can be readily classified or detected

Work supporting: Zeiler and Fergus, 2014; LeCun et al., 2015; Ritter et al., 2017.

Textural bias in deep CNNs

IMAGENET-TRAINED CNNS ARE BIASED TOWARDS TEXTURE; INCREASING SHAPE BIAS IMPROVES ACCURACY AND ROBUSTNESS

(a) Texture image		(b) Content image		(c) Texture-shape cue conflict	
81.4%	**Indian elephant**	71.1%	**tabby cat**	63.9%	**Indian elephant**
10.3%	indri	17.3%	grey fox	26.4%	indri
8.2%	black swan	3.3%	Siamese cat	9.6%	black swan

Geirhos et al., 2019.

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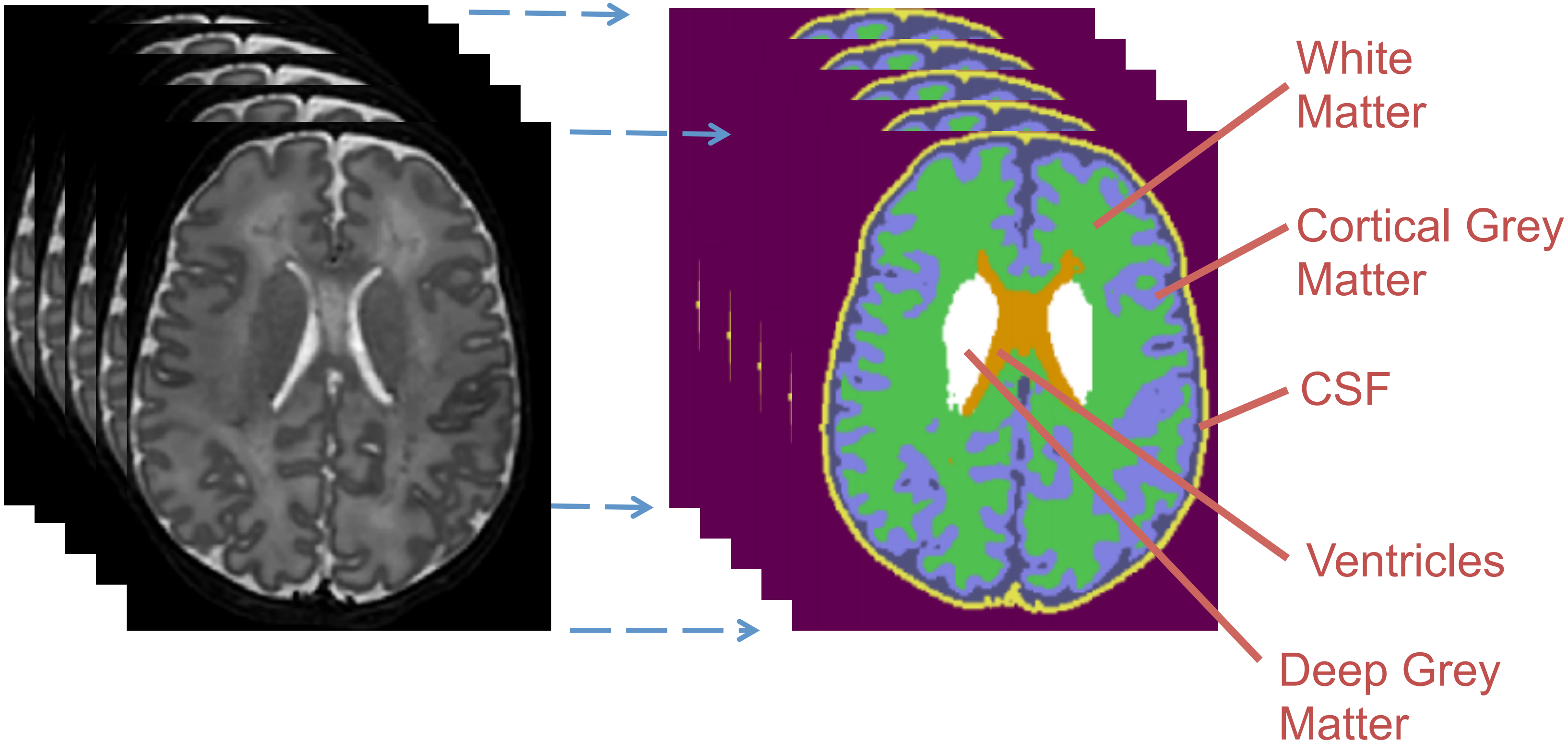
Segmentation of the developing brain with CNNs



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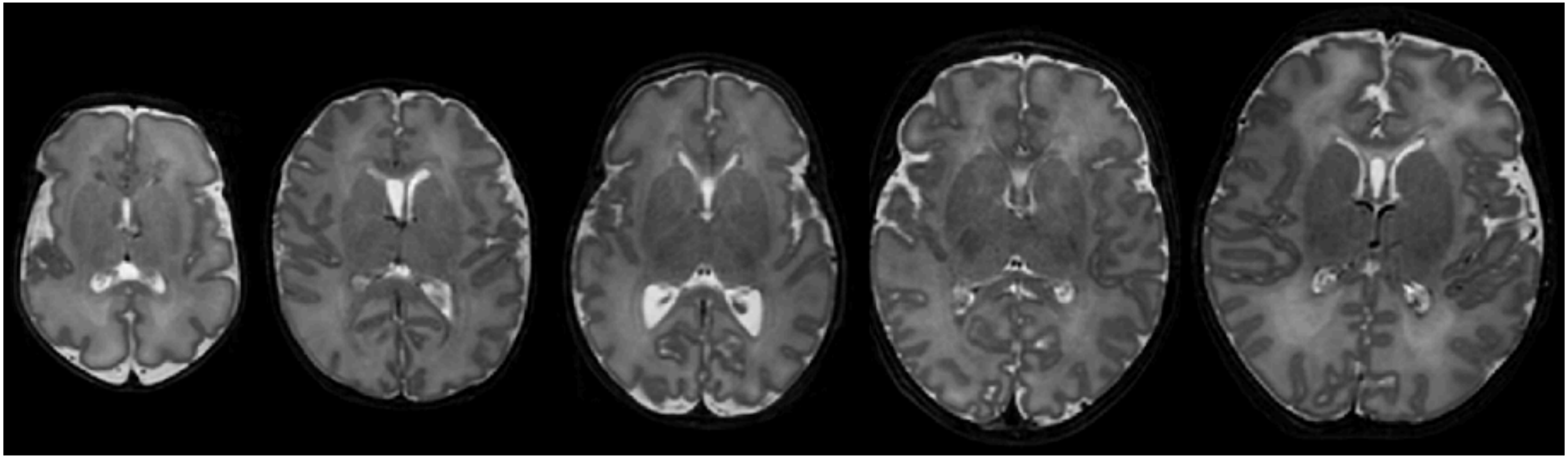
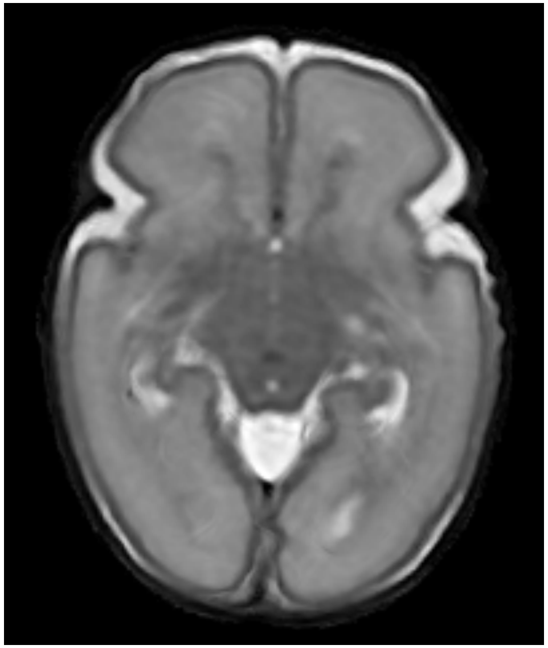
Challenge: Variation in both shape and texture



32 weeks 34 weeks 35 weeks 38 weeks 40 weeks

Context: Developmental brain mapping

e.g. The Developing Human Connectome Project (DHCP) aims to make major scientific progress by creating the first 4D connectome map of early life.



It is important to better understand the role of visual texture when developing CNNs on heterogeneous neonatal neuroimaging data.

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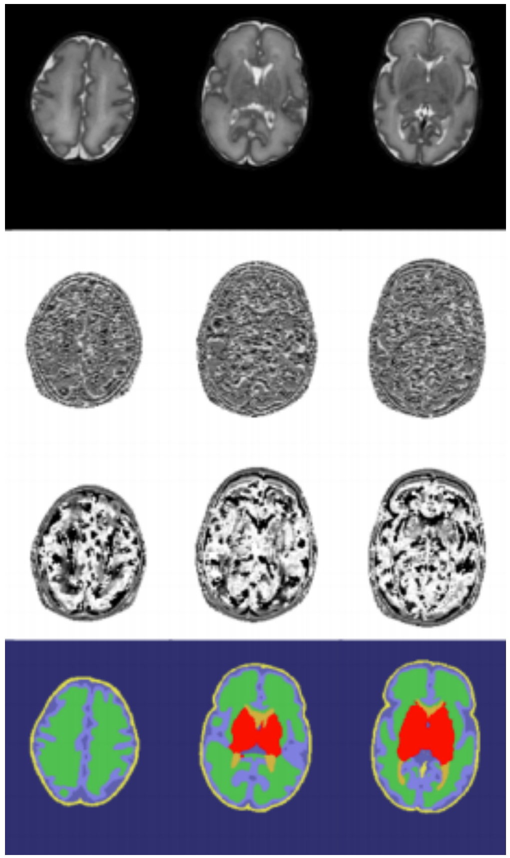
Our approach: Encoding with local textural patterns

T2-weighted:

LBP, 1 pixel:

LBP, 10 pixels:

Ground-truth:



$$LBP(x_c, y_c) = \sum_{p=0}^{P-1} f(i_p - i_c)2^p$$

$$f(x) = \begin{cases} 1 & if \quad x \geq 0 \\ 0 & , \quad otherwise \end{cases}$$

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Experimental set-up

Total data
558, 3D T2-weighted neonatal MRI scans, publicly available by DHCP.

Classes
1. Background, 2. CSF, 3. CGM, 4. WM, 5. Background bordering brain tissue, 6. Ventricles, 7. Cerebellum, 8. DGM, 9. Brainstem, 10. Hippocampus.

Labels
Segmentation maps available, output of the DHCP structural pipeline.

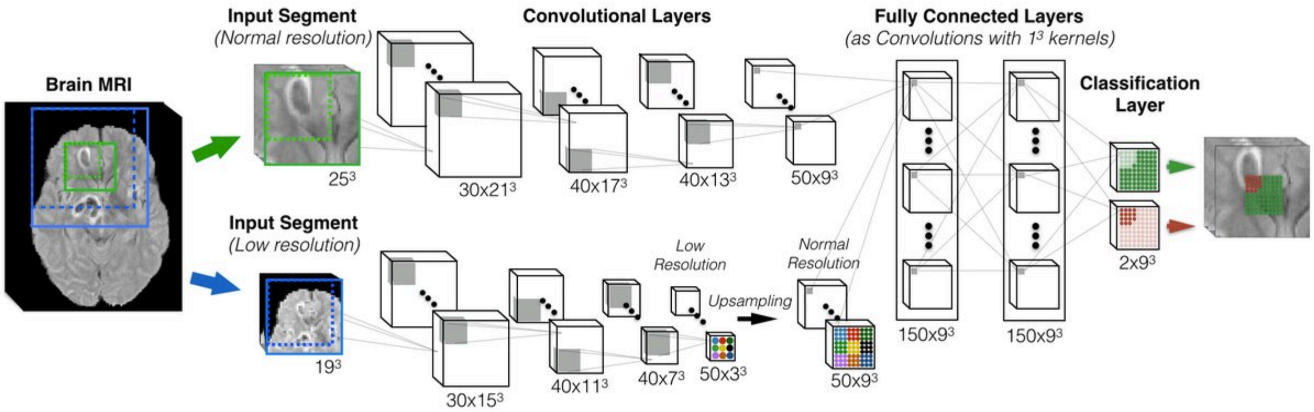
Model-development set
450 for training, PMA 24.7- 42.1 weeks.
20 for validation, PMA 27.6 - 42.2 weeks.

Held-out test set
88 for testing, PMA 24.3 – 42 weeks.

CNN
3D architecture developed with DeepMedic.

CNN architecture

- 3D modeling using DeepMedic

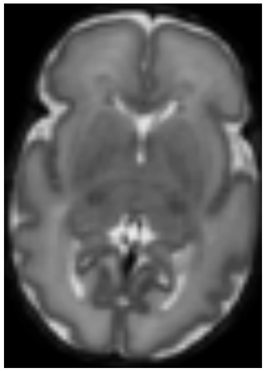


Kamnitsas et al. 2016.

- Three parallel pathways:
  - normal resolution
  - downsampled by 3
  - downsampled by 5
- 8 layers per pathway
- Training batch size was set to 5
- Learning rate followed a pre-defined schedule.

Three 3D CNNs

1



T2-weighted

2

LBP-encoded:
1 pixel distance

3

LBP-encoded:
10 pixel distance

*The goal is to train CNNs 2 and 3 on **explicit textural representations** generated from the T2-weighted images, and to evaluate performance in a complex tissue segmentation task.*

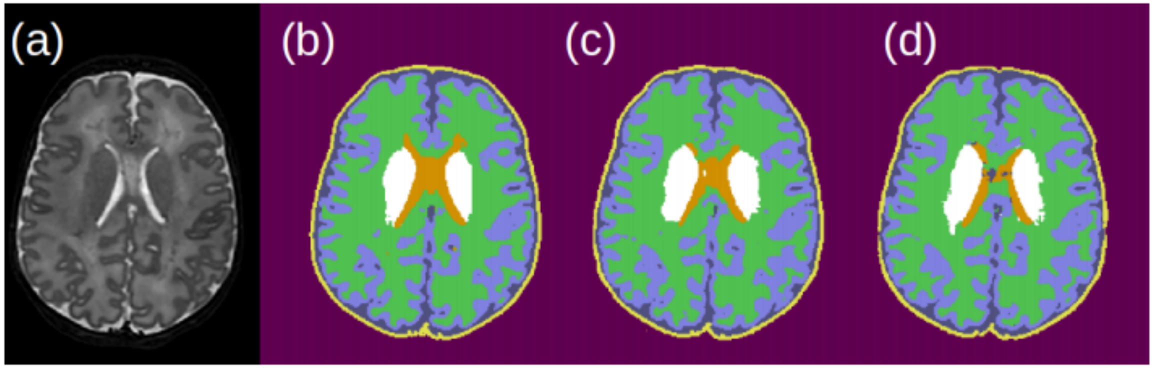
Summary of results

Classes: 1. Background, 2. CSF, 3. CGM, 4. WM, 5. Background bordering brain tissue, 6. Ventricles, 7. Cerebellum, 8. DGM, 9. Brainstem, 10. Hippocampus.

Using gray level intensities:
DSC: [0.9919, 0.9196, 0.9376, 0.9525, 0.8921, 0.8043, 0.9319, 0.9357, 0.9183, 0.7804].
Time for testing process: 11,193 seconds.

Using 10-pixel radius LBP maps:
DSC: [0.9869, 0.8825, 0.8949, 0.9221, 0.8458, 0.7610, 0.8954, 0.8926, 0.8377, 0.6505].
Time for testing process: 10,807 seconds.

Using 1-pixel radius LBP maps:
DSC: [0.9823, 0.8688, 0.9038, 0.9232, 0.8104, 0.6692, 0.7435, 0.7894, 0.5319, 0.0019].
Time for testing process: 11,101 seconds.



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Conclusion

The study is the ***first to show*** *on (neonatal) neuroimaging data that CNNs can indeed be trained on explicit textural representations of the data to achieve segmentation performance that is comparable to models trained on the original T2-weighted scans.*

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Thank you!
Questions?

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