University of Basel

Department of Biomedical Engineering

# Multi-Dimensional Gated Recurrent Units for the Segmentation of Biomedical 3D-Data

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Medical Image Analysis Center

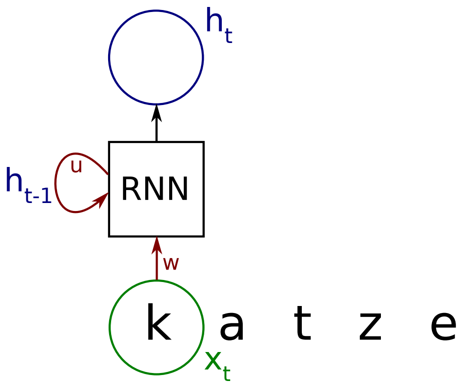
2nd Workshop on Deep Learning in Medical Image Analysis in Conjunction with MICCAI 2016

# RNN (Example)

## text to text: translation

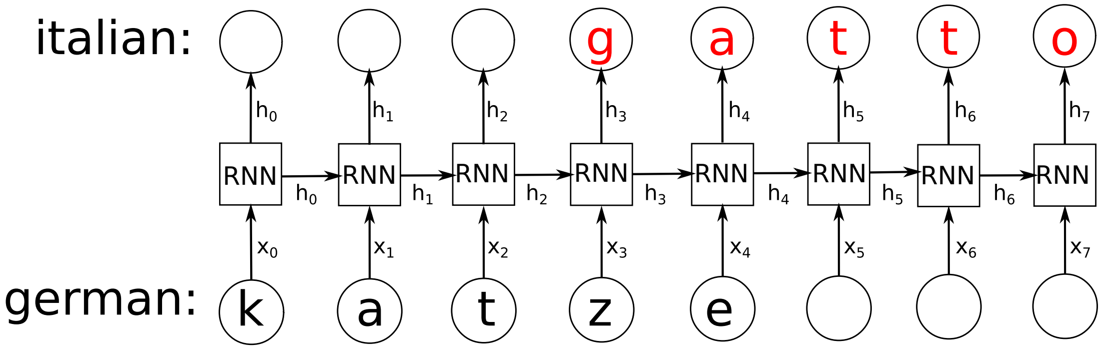
italian:

german:



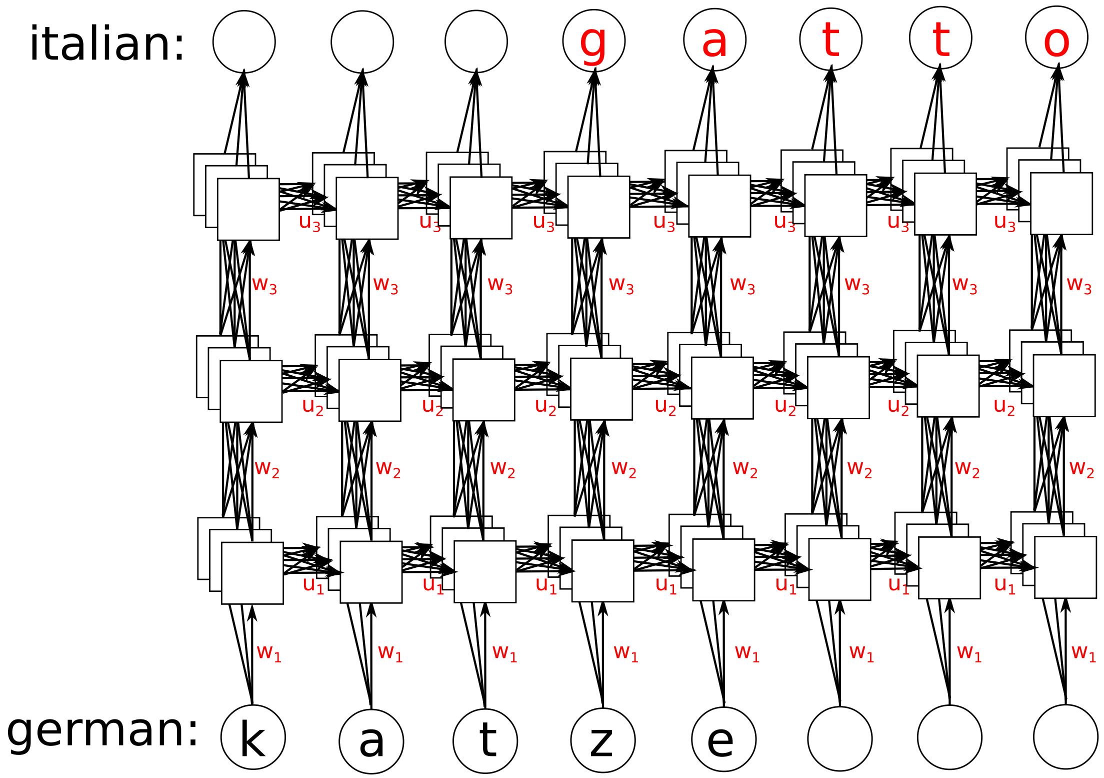
# RNN (Example)

## unfolded



# RNN (Example)

## more likely setup



# Vanishing Gradient Problem

| TanH | LSTM | GRU |
|---|---|---|
| • only one activation | • 3 gates, 1 state, 1 activation | • 2 gates, 1 state and activation |

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

# Generalization to Multiple Dimensions

⚡ Time is one-dimensional

- Each dimension individually as time dimension! [1]
- For each RNN layer:
  - Apply RNN along each dimension in each direction
  - Sum intermediate results

[1] Stollenga, M.F., Byeon, W., Liwicki, M., Schmidhuber, J.: *Parallel Multi- Dimensional LSTM, With Application to Fast Biomedical Volumetric Image Segmentation.* Advances in Neural Information Processing Systems 28, pp. 2998–3006. (2015)

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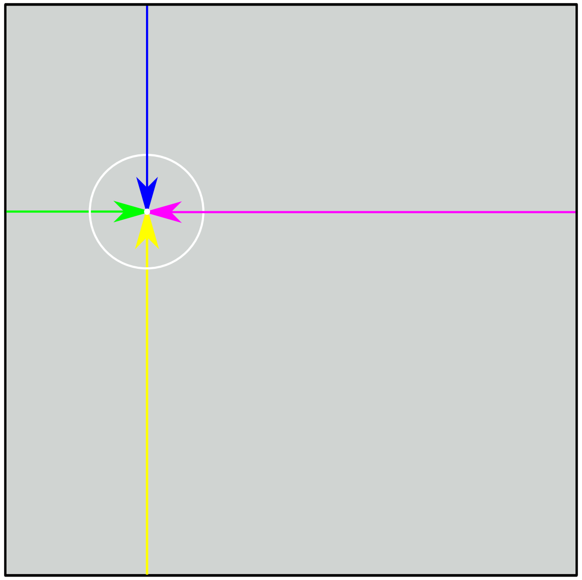
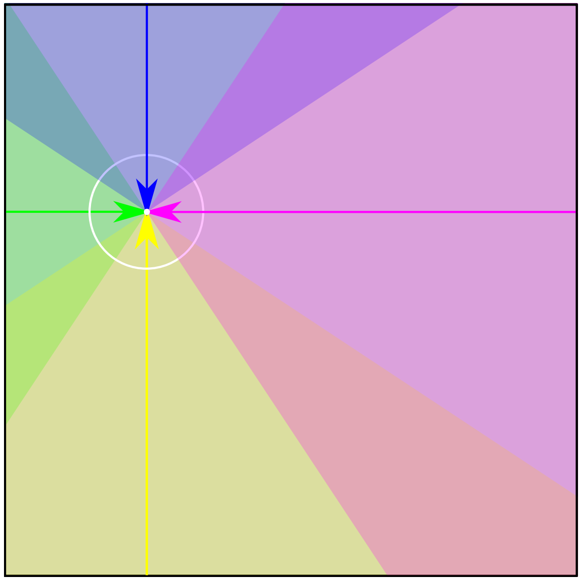
# MD-RNN Recurrent Connections (2D)

## Direct predecessor only



# MD-RNN Recurrent Connections (2D)

## Including **neighborhood** of predecessor (convolution)



# Convolutional Gated Recurrent Unit (C-GRU)

MD-GRU Layer: 1 C-GRU for each direction & dimension

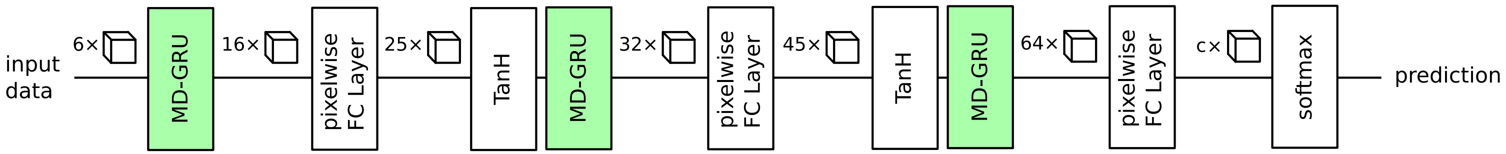
$$r^j = \sigma\left(\sum_i^I (x^i * w_r^{i,j}) + \sum_k^J (h_{t-1}^k * u_r^{k,j}) + b_r^j\right),$$

$$z^j = \sigma\left(\sum_i^I (x^i * w_z^{i,j}) + \sum_k^J (h_{t-1}^k * u_z^{k,j}) + b_z^j\right),$$

$$\tilde{h}_t^j = \phi\left(\sum_i^I (x^i * w^{i,j}) + r^j \odot \sum_k^J (h_{t-1}^k * u^{k,j}) + b^j\right),$$

$$h_t^j = z^j \odot h_{t-1}^j + (1 - z^j) \odot \tilde{h}_t^j.$$

# Network




- Caffe 1.0 rc3
- Custom layers using CuDNN v5

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# MrBrains13 challenge

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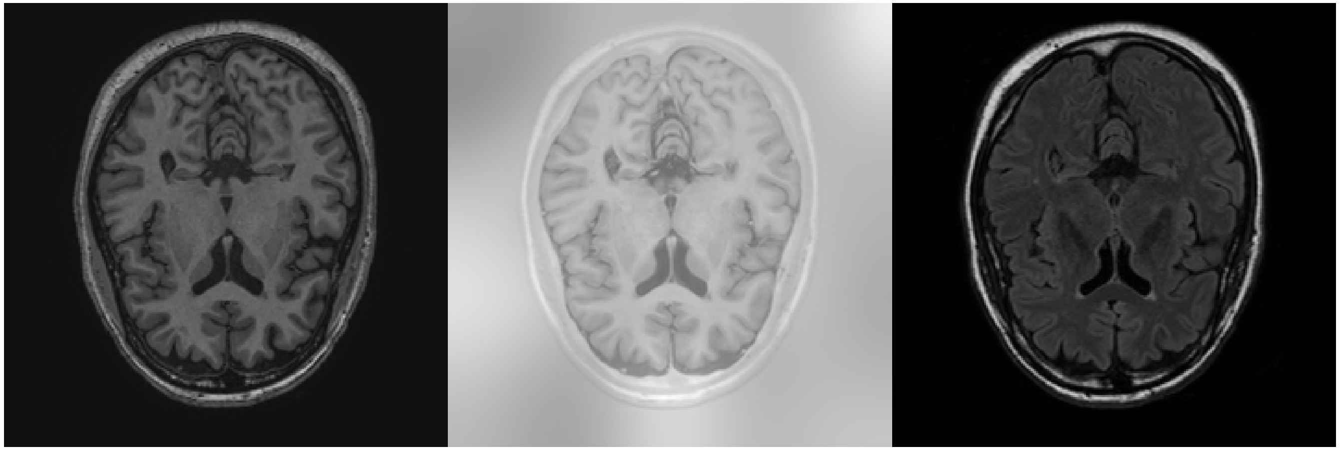
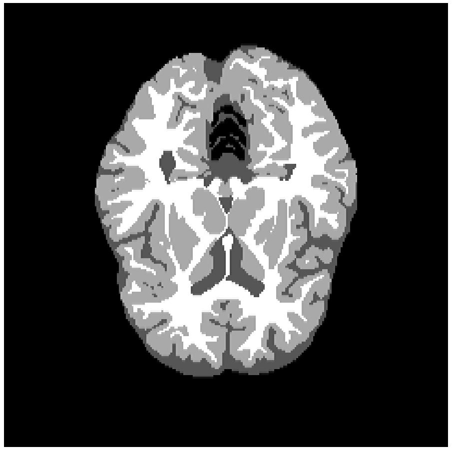
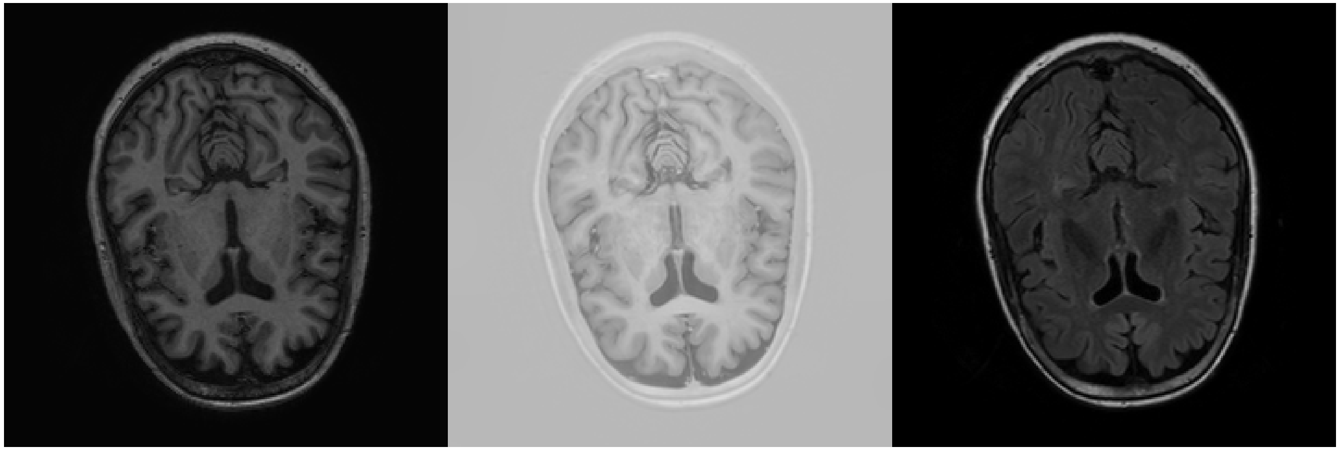
## Training data (5 patients)



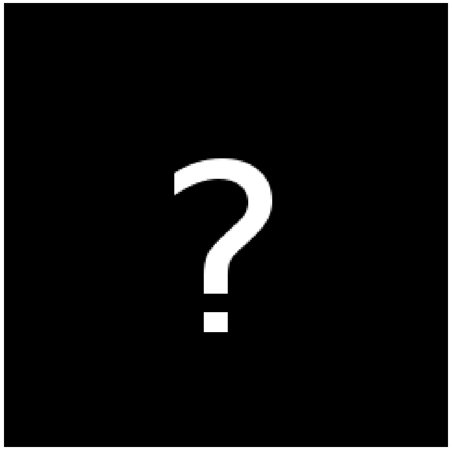
## Training labels



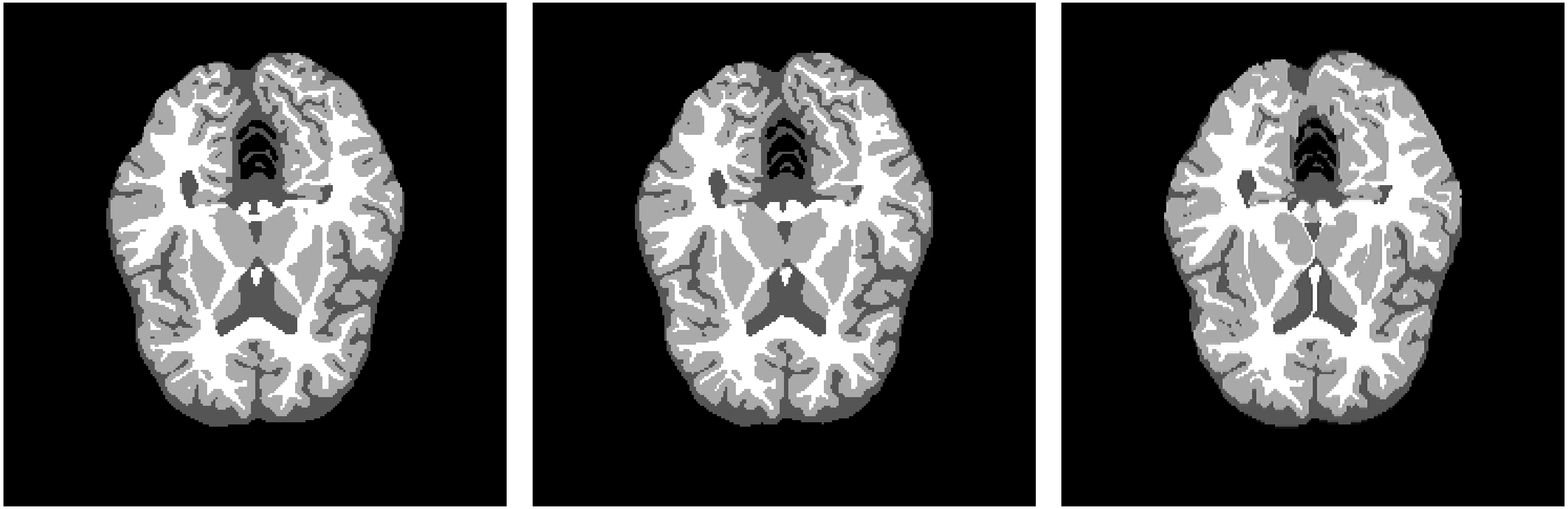
## Testing data (15 patients)



## Estimation



# MD-GRU / MD-LSTM [1]



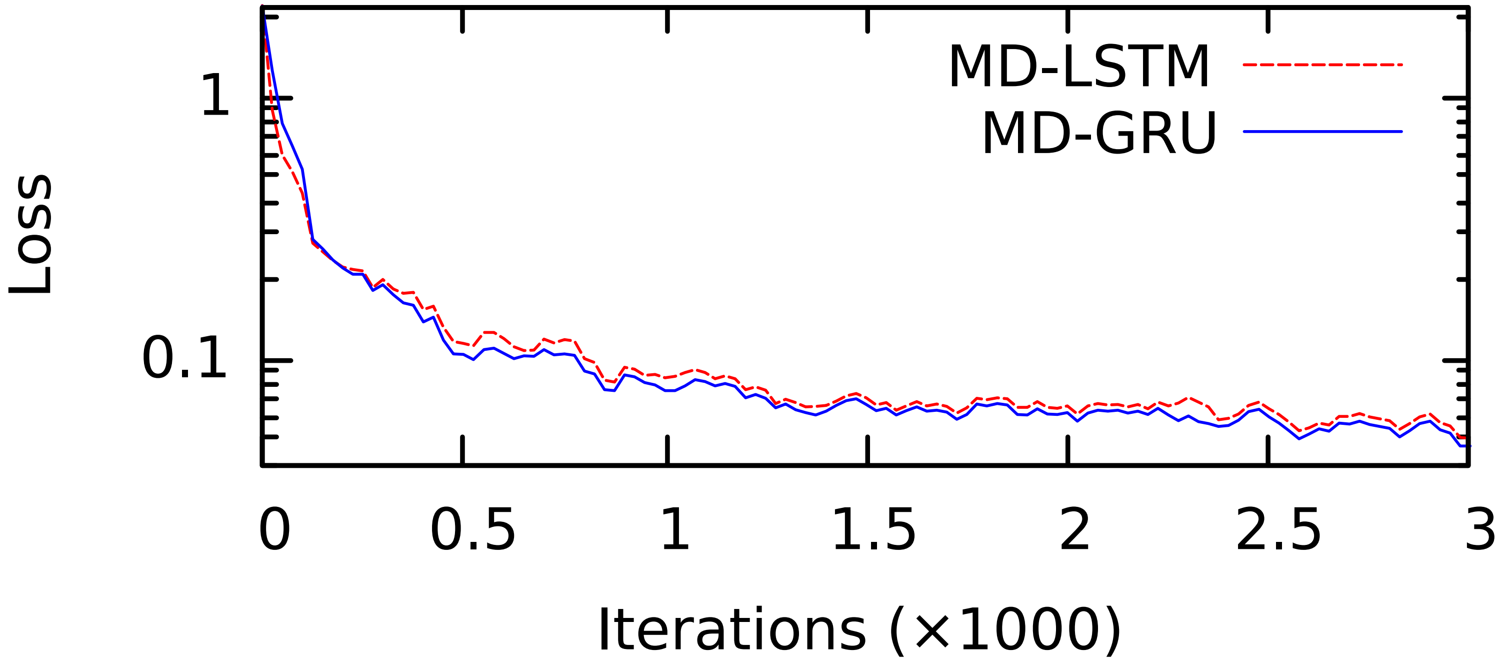
a: MD-LSTM b: MD-GRU c: Training labels

[1] Stollenga, M.F., Byeon, W., Liwicki, M., Schmidhuber, J.: *Parallel Multi- Dimensional LSTM, With Application to Fast Biomedical Volumetric Image Segmentation.* Advances in Neural Information Processing Systems 28, pp. 2998–3006. (2015)

# MD-GRU / MD-LSTM

| | GM | WM | CSF | ICV |
|---|---|---|---|---|
| MD-LSTM | **88.09** | 90.08 | 82.62 | 97.56 |
| MD-GRU | 87.88 | **90.15** | **83.19** | **97.73** |

# MD-GRU / MD-LSTM




MD-LSTM: 12.8 s / MD-GRU: 9.1 s per iteration

(volume of 192 × 192 × 14)

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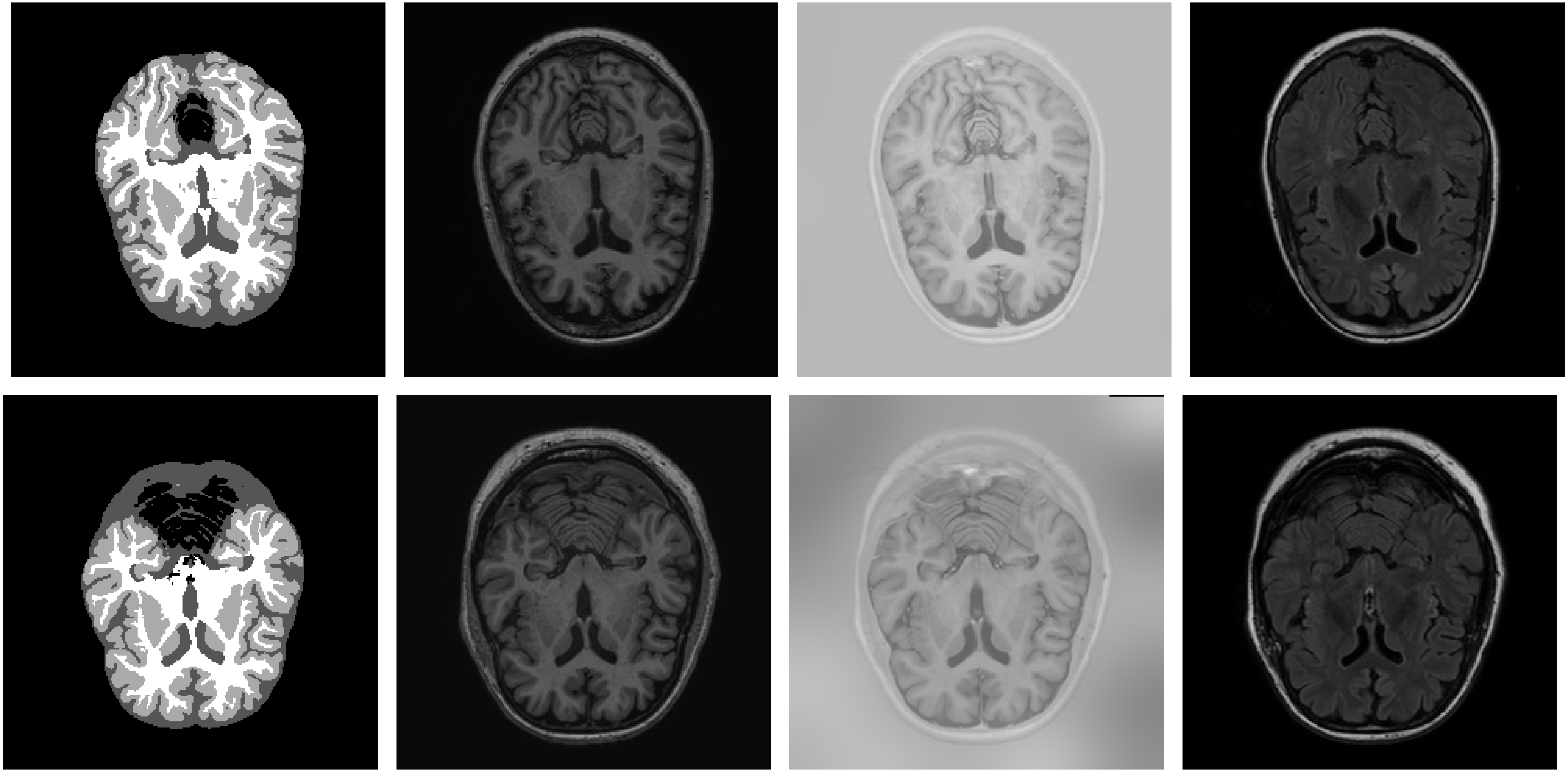
# MD-GRU Challenge Results



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# MD-GRU Challenge Results

| Team name | Rank | GM | | | WM | | | CSF | | | ICV | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Dice | HD | AVD | Dice | HD | AVD | Dice | HD | AVD | Dice | HD | AVD |
| CU_DL2 [3] | **1** | **86.15** | **1.45** | 6.60 | **89.46** | **1.94** | 6.05 | **84.25** | 2.19 | 7.69 | 98.10 | 2.75 | 1.54 |
| CU_DL [3] | 2 | 86.12 | 1.47 | 6.42 | 89.39 | **1.94** | **5.84** | 83.96 | 2.28 | 7.44 | 97.99 | 3.16 | 1.83 |
| MD-GRU [Ours] | 3 | 85.40 | 1.55 | **6.09** | 88.98 | 2.02 | 7.69 | 84.13 | 2.17 | 7.44 | **98.15** | **2.37** | 0.86 |
| PyraMiD-LSTM2 ([2]) | 4 | 84.89 | 1.67 | 6.35 | 88.53 | 2.07 | 5.93 | 83.05 | 2.30 | 7.17 | 98.04 | 2.86 | **0.69** |
| FBI/LMB Freiburg [2] | 5 | 85.44 | 1.58 | 6.60 | 88.86 | 1.95 | 6.47 | 83.47 | 2.22 | 8.63 | 97.98 | 2.51 | 1.06 |
| IDSIA [1] | 6 | 84.82 | 1.70 | 6.77 | 88.33 | 2.08 | 7.05 | 83.72 | **2.14** | **7.09** | **98.15** | 2.44 | 0.95 |

[1] Stollenga, M.F., Byeon, W., Liwicki, M., Schmidhuber, J.: *Parallel Multi- Dimensional LSTM, With Application to Fast Biomedical Volumetric Image Segmentation.* Advances in Neural Information Processing Systems 28, pp. 2998–3006. (2015)

[2] Çiçek, Ö., Abdulkadir, A., Lienkamp, S.S., Brox, T., Ronneberger, O.: *3d U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation.* arXiv:1606.06650 [cs] (Jun 2016)

[3] Chen, Hao, et al. *VoxResNet: Deep Voxelwise Residual Networks for Volumetric Brain Segmentation.* arXiv preprint arXiv:1608.05895 (2016).

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# Acknowledgements

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