

Five-layer Deep Convolutional Neural Network applied to middle-most cross sections for predicting the presence of MGMT promoter methylation in FLAIR MRI scans

BraTS Challenge 2021: RSNA-MICCAI Brain Tumor Radiogenomic Classification

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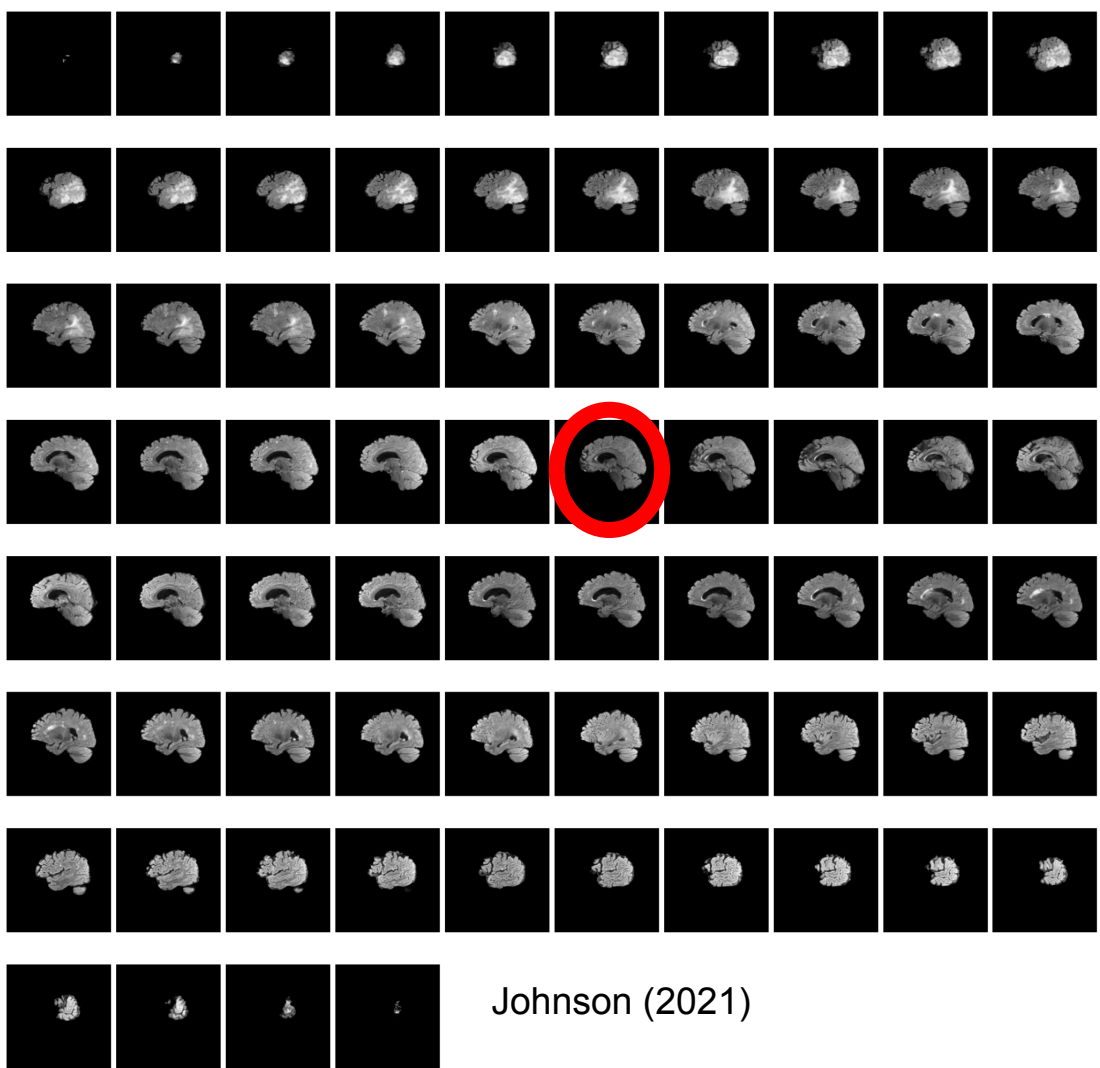
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Data Sampling

Pick the “most important image”.

For each training sample, pick the middle most FLAIR cross-section.

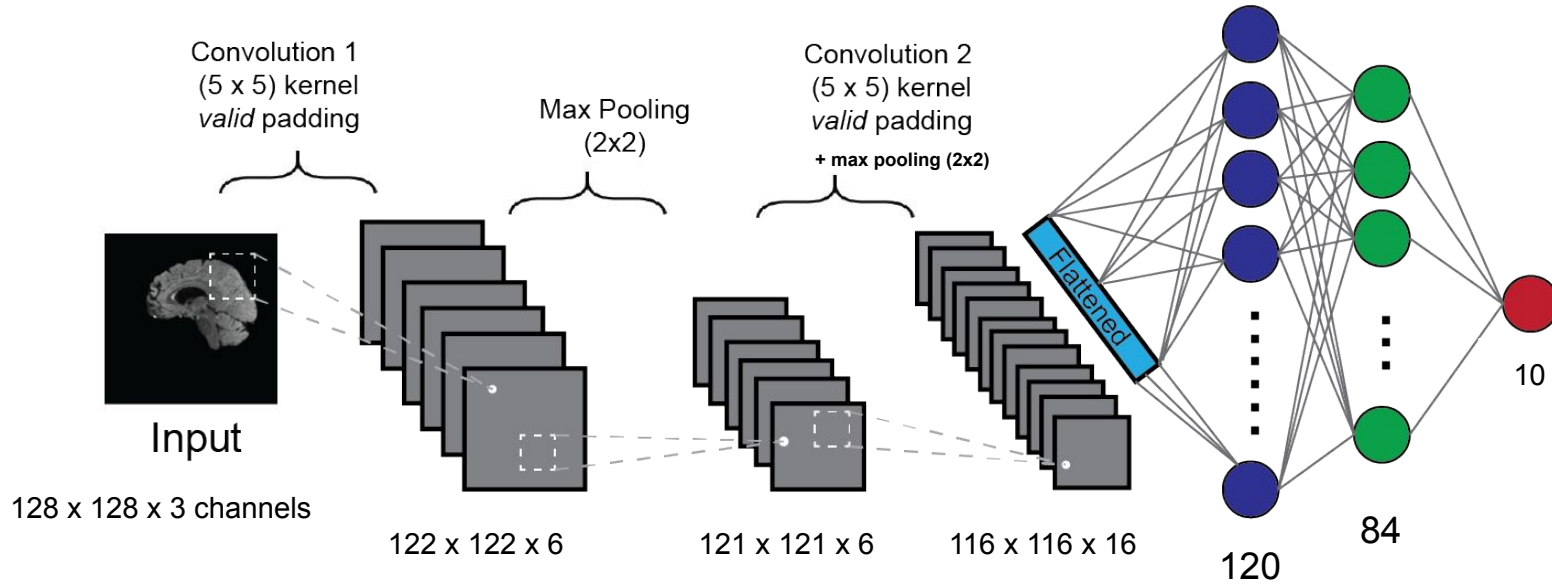
“Middle-most” here means when lining up the cross sections from front to back as shown to the right.



Johnson (2021)

Neural Network

Leaky ReLU activations between each layer



Training and Cross Validation

Train using a One Cycle policy, Adam optimizer. Batch size of 64. Loss function: Categorical Cross Entropy.

The model was able to **learn**, validation loss decreases after the 3rd epoch.

Comment: It may have been better to stop at the 5th epoch.

epoch	train_loss	valid_loss	error_rate	accuracy	time
0	1.179571	0.674959	0.413793	0.586207	00:02
1	1.108988	0.729703	0.586207	0.413793	00:02
2	1.076067	0.665072	0.396552	0.603448	00:02
3	1.050501	0.963969	0.586207	0.413793	00:03
4	1.027446	0.749877	0.508621	0.491379	00:02
5	1.000942	0.680456	0.405172	0.594828	00:02
6	1.002666	0.681733	0.413793	0.586207	00:02
7	0.978674	0.697218	0.474138	0.525862	00:02
8	0.965975	0.710260	0.508621	0.491379	00:02
9	0.951226	0.704067	0.517241	0.482759	00:02

Results

Kaggle Competition Public test set performance: area of 0.616 under the ROC curve between the predicted probability and the observed target

Contrastly, two alternatives we tried:

- Feature engineered solution counting the number of dark points or light points, or ratios thereof

- 20-layer deep nets with 20+ cross sections as input

Both performed *worse* (< 0.45 area under ROC curve) (Chen et. al. 2021).

Therefore, it seems that training on less features is better.

Rationale: There are less than 500 unique patient scans, each with about 500+ cross sections. So there are lots of features/dimensions per training sample but not enough training samples themselves. Sampling the middle-most cross section has a **regularization** effect similar to Dropout layers.

Works Cited

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2. Nicholas Johnson: Initial Notebook Brain Tumour, <https://www.kaggle.com/nicholasjohnson2020/initial-notebook-brain-tumour>. Last accessed 8 Aug 2021
3. B. H. Menze, A. Jakab, S. Bauer, J. Kalpathy-Cramer, K. Farahani, J. Kirby, et al. "The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)", IEEE Transactions on Medical Imaging 34(10), 1993-2024 (2015) DOI:10.1109/TMI.2014.2377694
4. Chen, Daniel T, et al. "RSNA-MICCAI Competition -- Dynamic Programming." *Kaggle*, Kaggle, 31 Aug. 2021, www.kaggle.com/d223chen/rsna-miccai-competition-dynamic-programming. Last accessed 12 Sep 2021
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