

Automated segmentation of WMHs

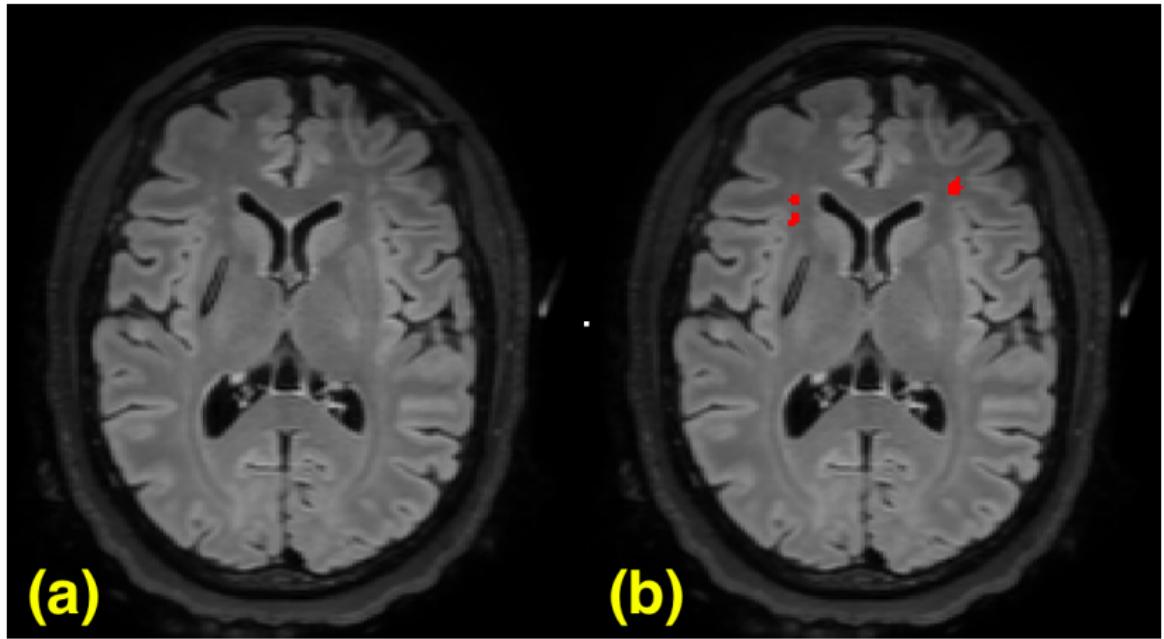
Current status and future directions

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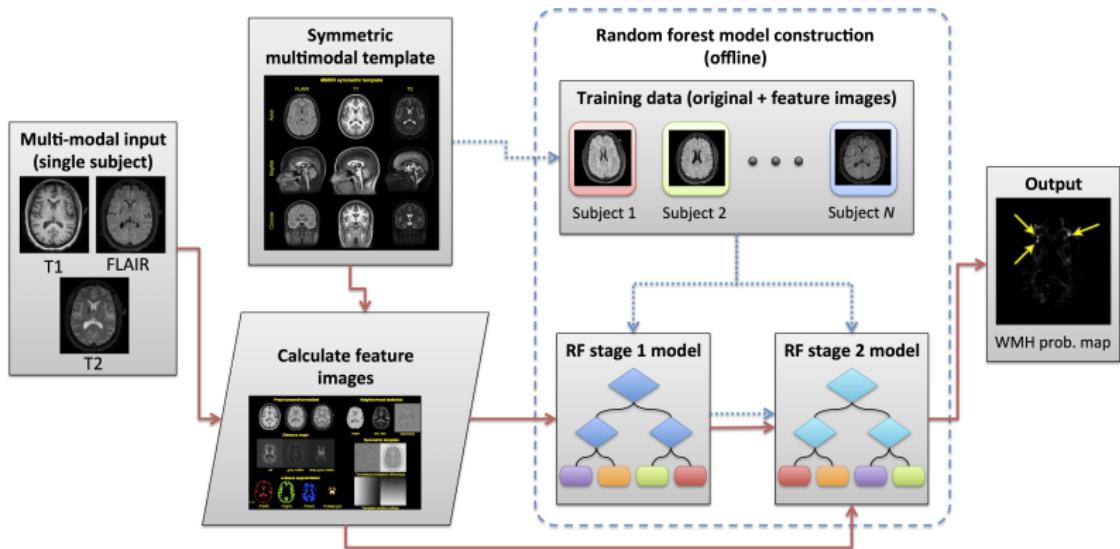
August 11, 2017

WMH segmentation



Current pipeline

Stone et al. *Supervised learning technique for the automated identification of white matter hyperintensities in traumatic brain injury*, March, 2016.

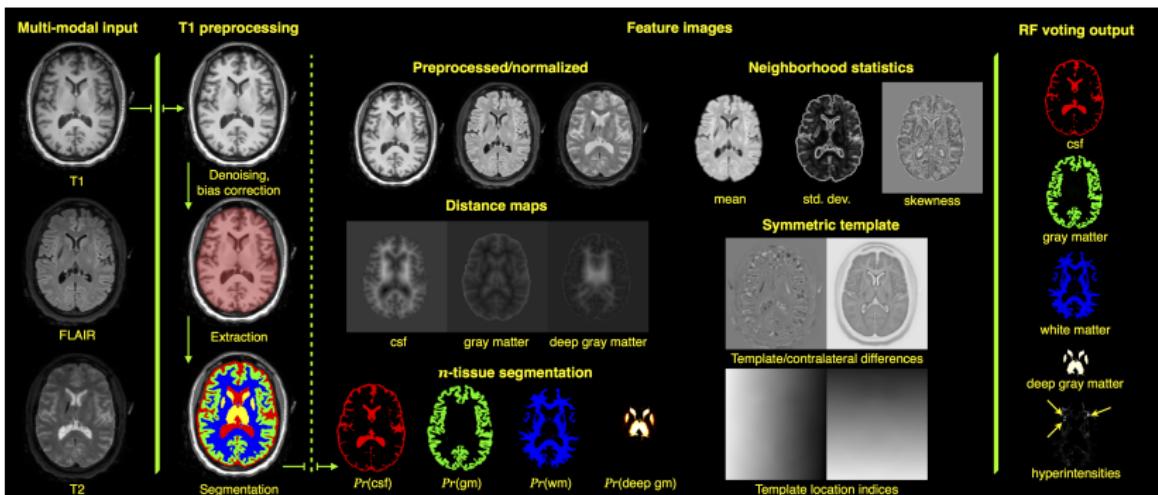


Features

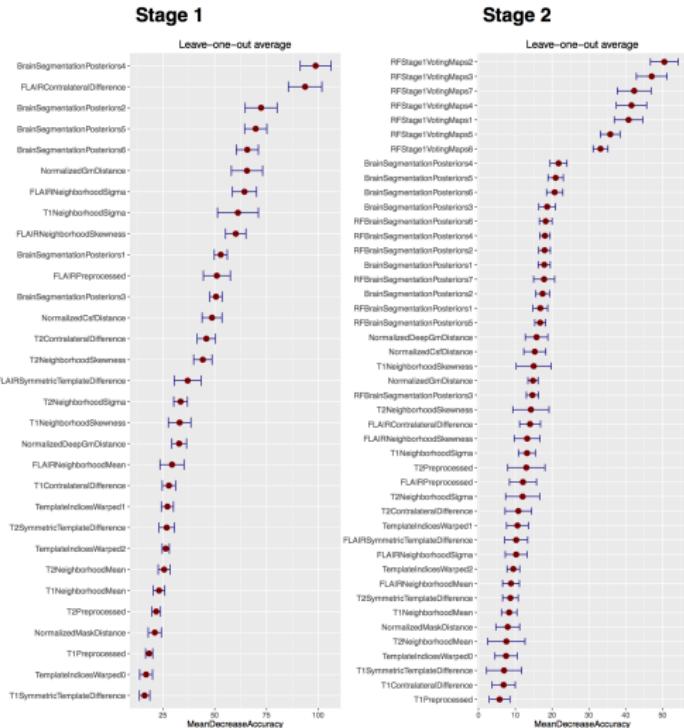
Feature type	Image source	Name
Intensities		
normalized/preprocessed	FLAIR, T1, and T2	Preprocessed
Symmetric template		
template difference	FLAIR, T1, and T2	SymmetricTemplateDifference
contralateral difference	FLAIR, T1, and T2	ContralateralDifference
template location indices	FLAIR, T1, and T2	TemplateIndicesWarped
Segmentation probabilities		
$Pr(\text{cerebrospinal fluid})$	T1	BrainSegmentationPosterior1
$Pr(\text{gray matter})$	T1	BrainSegmentationPosterior2
$Pr(\text{white matter})$	T1	BrainSegmentationPosterior3
$Pr(\text{deep gray matter})$	T1	BrainSegmentationPosterior4
$Pr(\text{brain stem})$	T1	BrainSegmentationPosterior5
$Pr(\text{cerebellum})$	T1	BrainSegmentationPosterior6
Distance maps		
cerebrospinal fluid	T1 brain segmentation	NormalizedCsfDistance
gray matter	T1 brain segmentation	NormalizedGmDistance
deep gray matter	T1 brain segmentation	NormalizedDeepGmDistance
whole brain	T1 brain segmentation	NormalizedMaskDistance
Neighborhood statistics		
mean	FLAIR, T1, and T2	NeighborhoodMean
standard deviation	FLAIR, T1, and T2	NeighborhoodSigma
skewness	FLAIR, T1, and T2	NeighborhoodSkewness

Feature images

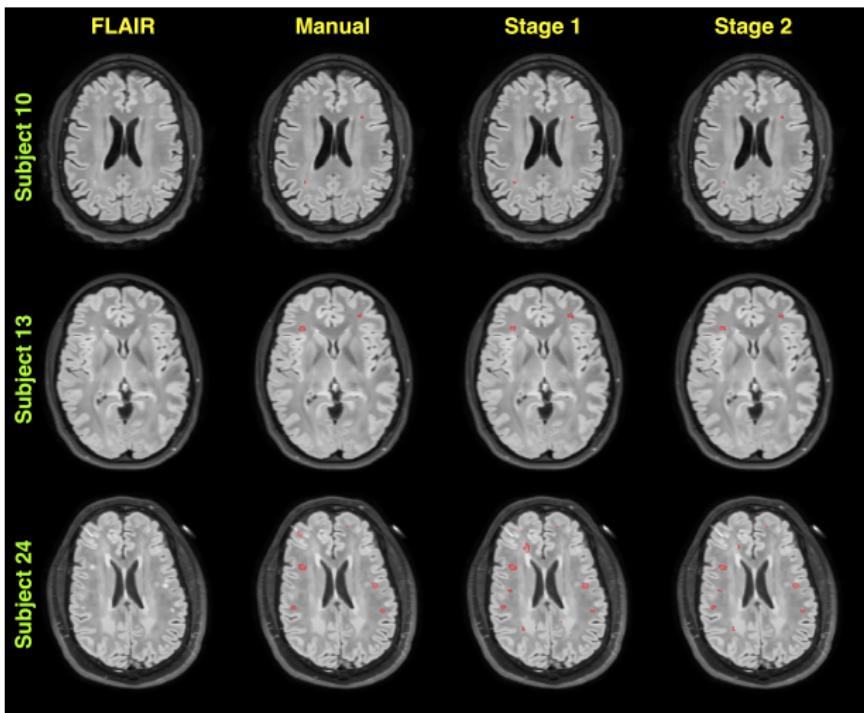
$$\text{label} \sim_{RF} \text{feature}_1 + \dots + \text{feature}_n$$



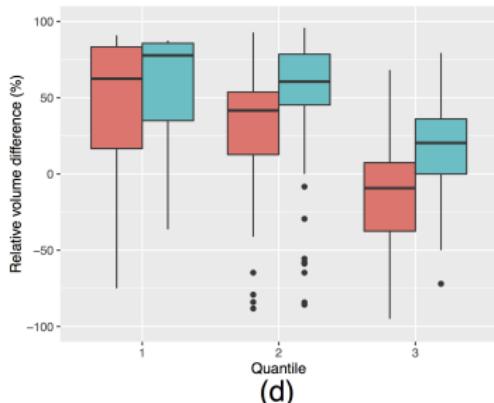
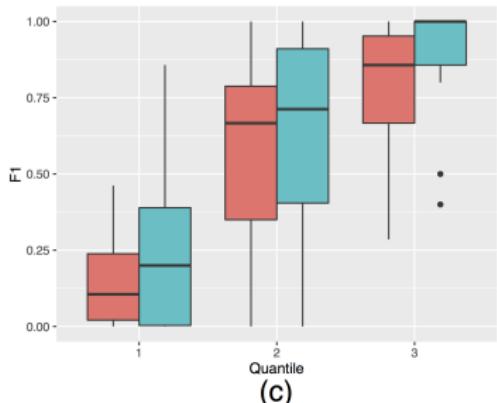
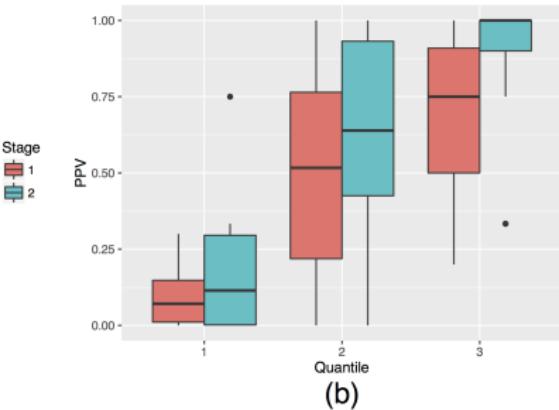
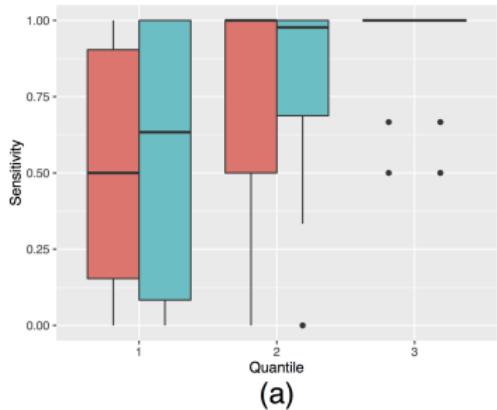
Feature importance



Sample results: Site 1



Leave-one-out evaluation



Problems with current approach

- Takes a lot of time for new data
 1. Create initial set of feature images
 2. Run it through Stage 1 model
 3. Create more feature images
 4. Run subject through Stage 2 model
- We are using a relatively small training data set
- Modeling/training is limited to a single site
- Creative engineering is needed
 - Feature image selection
 - Are we choosing discriminative features?
- We have imbalanced data (e.g., way more GM than WMH voxels)
- No comparisons with clinical data (yet)

What about deep learning?

- Exciting new possibilities with deep learning
- Potentially quicker for new data
 - Building initial model takes time **but**
 - no feature images are needed to create for new data.
- Optimization and architecture are used to learn the features
- Mature packages
 - TensorFlow, CNTK, Torch, Theano, Sci-TK, Caffe, mxnet, Keras
- Need lots of training data

Current work

1. Rebuild RF models from Site 1 balanced data ←
2. Employ all CENC data ←
3. Apply RF approach ←
4. Check clinical correlations
5. Manually refine data from 2.
6. Re-check clinical correlations
7. Use data from 5. to train deep learning model
8. Re-check clinical correlations

Quick note on imbalanced data

- 7 tissue voxel labels
 - CSF ($n = 208080, 18\%$)
 - gray matter ($n = 457437, 39\%$)
 - white matter ($n = 317788, 27\%$)
 - deep gray matter ($n = 33042, 2.8\%$)
 - brain stem ($n = 17975, 1.5\%$)
 - cerebellum ($n = 1369656, 12\%$)
 - WMH ($n = 901, 0.07\%$)
- SMOTe (Synthetic Minority Over-sampling Technique)
 - For “rare” events: $\leq 15\%$
 - use bootstrapping and k -nearest neighbor