ON-LINE APPENDIX

Textural Feature Description

We extracted a total number of 376 image features for each ASPECT region in 3D for both the ischemic and contralateral sides. All the texture features were implemented in Matlab R2016.

First-Order Statistics. First-order statistics (36 features) describe the distribution of voxel intensities within the CT image. The selected measures were mean, SD, median, minimum, maximum, entropy, mode, energy, the first 7 standardized moments around the mean, a normalized histogram of 20 bins ranging from 0 to 100 for NCCT images, the histogram bin with the highest count, skewness, and kurtosis.[1]

Gray-Level Co-Occurrence Matrix. Gray-level co-occurrence matrix (GLCM) 78 features, also known as the gray-level spatial dependence matrix, characterizes the texture of an image by calculating how often pairs of pixels with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. In this article, co-occurrences with a distance of 1 pixel were calculated in horizontal, vertical, and diagonal orientations ($\theta = 0, 45, 90, 135$) for intensity bins with width 5 for NCCT images. For the axial, coronal, and sagittal planes, 1 co-occurrence matrix was constructed including all slices, and the mean and SD of the 4 orientations were calculated per plane for 13 measures, such as autocorrelation, contrast, correlation, cluster prominence, dissimilarity, energy, entropy, homogeneity, maximum probability, sum average, sum entropy, and 2 information measures of correlation.[2]

Gray-Level Run Length. Rather than looking at pairs of pixels, the gray-level run length (GLRL, 66 features) looks at runs of pixels—that is, how many pixels of a given gray value occur in a sequence in a given direction.[3] In this article, runs with $\theta = 0$, 45, 90, and 135 were calculated in the axial, coronal, and sagittal views. Measures, such as short-run emphasis, long-run emphasis, gray-level nonuniformity, run-length nonuniformity, run percentage, low gray-level run emphasis, high gray-level run emphasis, short-run low gray-level emphasis, short-run high gray-level emphasis, long-run low gray-level emphasis, and long-run high gray-level emphasis were calculated and averaged over the 4 orientations for each plane. All measures were calculated for both intensity bins of width 5 for NCCT images.[4,5]

Neighboring Gray-Tone Difference Matrix. The neighboring gray-tone difference matrix (NGTDM, 10 features) is based on the differences between each voxel and the neighboring voxels in the adjacent image planes.[6] Texture parameters derived from NGTDM resemble the human perception of the image. Five measures of coarseness, contrast, busyness, complexity, and strength were calculated. We calculated the mean difference with the surrounding voxels in a 3D 26 neighborhood, for intensity bins of 1 and 10. The 5 measures were calculated for both of these settings and both image modalities.

Laws Texture. Laws 105 features measures texture energy by convolution of the image with 1D kernels.[7] We used five 1D kernels: $(1, 4, 6, 4, 1)$ (level, L), $(-1, -2, 0, 2, 1)$ (edge, E), $(-1, 0, 2, 0, -1)$ (spot, S), $(1, -4, 6, -4, 1)$ (ripple, R) and $(-1, 2, 0, -2, 1)$ (wave, W), which created 125 3D kernels: Level-Level Spot (LLS), level-level edge (LLE), and so forth. After convolution, the mean, absolute mean, and SD over the ROI and averaged measures of rotated kernels were calculated after convolution. This yielded 35 kernels with 3 measures each.

Local Binary Pattern. Local binary pattern (LBP, 27 features) is a type of visual descriptor for classification in computer vision. LBP is the particular case of the texture spectrum model,[8,9] and a powerful feature for texture classification. LBP measures the homogeneity of texture by determining the number of transitions from intensities higher than each central pixel to intensities lower than that central pixel. In this study, the number of "regions" higher or lower in intensity around each voxel in a 26 and 98 neighborhood were applied. The mean and SD of the number of regions were calculated.

First-Order Statistics after Gaussian Filtering. Twenty-one first-order statistics features were additionally calculated after smoothing images using a 3D Gaussian kernel at 2 scales of 0.16 and 0.32 mm. Those features (42 features) are mean, SD, median, minimum, maximum, entropy, mode, energy, skewness, kurtosis, and the histogram bins with the highest count.

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On-line Table: **Top 5 features and parameters used for random forest learning for each ASPECTS region**[a]

Region/Names of the Top 5 Features	No. of Trees	Maximum Depth of Tree	No. of Ranked Features	Class Weight (Abnormal/ Normal)
M1				
Median	5	5	8	4.5:1
First bin in histogram				
Second bin in histogram				
Short-run emphasis of GLRLM with the level of 30 at coronal orientation				
M2				
Short-run high gray-level emphasis of GLRLM with the level of 30 at sagittal orientation				
Short-run low gray-level emphasis of GLRLM with the level of 120 at axial orientation	14	11	39	1.5:1
Long-run low gray-level emphasis of GLRLM with the level of 120 at sagittal orientation				
Short-run high gray-level emphasis of GLRLM with the level of 120 at coronal orientation				
Long-run low gray-level emphasis of GLRLM with the level of 120 at coronal orientation				
Complexity of NGTDM with the level of 600				
M3				
Autocorrelation of GLCM at axial plane	5	14	32	6.0:1
Sum of average of GLCM at axial plane				
M4				
Sum of average of GLCM at coronal plane				
Contrast of GLCM at sagittal plane				
Sum of average of GLCM at sagittal plane				
Sum of average of GLCM at axial plane	8	8	20	7.0:1
Sum of average of GLCM at coronal plane				
Long-run low gray-level emphasis of GLRLM with the level of 120 at axial orientation				
Long-run low gray-level emphasis of GLRLM with the level of 30 at axial orientation				
M5				
Short-run high gray-level emphasis of GLRLM with the level of 120 at coronal orientation	8	8	38	1.3:1
Nonuniformity of GLRLM with the level of 30 at axial orientation				
Short-run emphasis of GLRLM with the level of 30 at coronal orientation				
Long-run emphasis of GLRLM with the level of 30 at coronal orientation				
Nonuniformity of GLRLM with the level of 30 at coronal orientation				
M6				
Entropy of GLCM at axial plane	5	5	5	5.9:1
Sum of entropy of GLCM at axial plane				
Mean of entropy of GLCM at axial plane				
Mean of entropy of GLCM at coronal plane				
Sum of entropy of GLCM at coronal plane				
GLRL_Axial_30_short run high gray-level emphasis				
L				
Mean	8	5	28	2:1
Energy				
Long-run emphasis of GLRLM with the level of 30 at sagittal orientation				
Mean after Gaussian filtering at scale 1				
Mean after Gaussian filtering at scale 2				
Mean after Gaussian filtering at scale 3				
I				
Absolute mean of LLE of Laws	20	11	27	0.9:1
Absolute mean of LLS of Laws				
Absolute mean of LEE of Laws				
Absolute mean of LES of Laws				
SD of LLE of Laws				
C				
Median	11	5	45	2.4:1
Energy				
Autocorrelation of GLCM at axial plane				
Autocorrelation of GLCM at coronal plane				
Autocorrelation of GLCM at sagittal plane				
Short-run emphasis of GLRLM with the level of 30 at axial orientation	5	8	5	5.9:1
Long-run emphasis of GLRLM with the level of 30 at axial orientation				
Short-run emphasis of GLRLM with the level of 30 at coronal orientation				
Long-run emphasis of GLRLM with the level of 30 at coronal orientation				
Mean after Gaussian filtering at scale 3				

Note:—L indicates lentiform; I, insula; C, caudate; IC, internal capsule; GLRLM, gray-level run-length matrix; NGTDM, neighborhood gray-tone difference matrix; LLE, level-level edge; LLS, level-level spot; LEE, level-edge edge; LES, level-edge spot.

[a] Most of these features are high-order texture features.