Alzheimer’s disease state classification using structural volumetry, cortical thickness and intensity features

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Overview

Training Data
(ADNI1/2)

Preprocessing
(CAAD data)

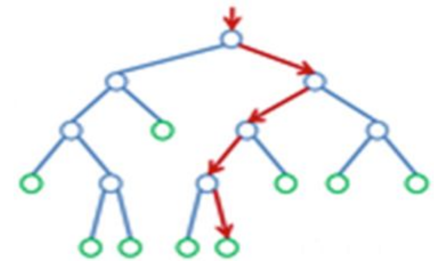
Feature extraction

Volumetric features
Cortical features

Manifold-based learning

Patch-based grading

Classification
(Random Forest)



Healthy/MCI/AD?

Results
(ADNI, CAAD training)

Overview

Training Data
(ADNI1/2)

Training Data (n=734)

Table 1: Subject groups mean age, sample size, MMSE scores, gender, CDR scores and Magnetic strength from ADNI1-2.

	N	Age	MMSE	Men (#)	CDR	1.5T (3T)
AD	170	74.77±7.62	23.12±2.06	46% (78)	0.79±0.27	90 (80)
MCI	288	73.79±7.47	27.28±1.79	55% (158)	0.50±0.00	185 (103)
CN	276	74.75±5.82	29.07±1.16	47% (131)	0.00±0.00	156 (120)

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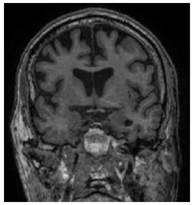

Data Preprocessing

- Scans with in-plane resolution <0.5mm were resampled
  → double resolution
- N4 bias field correction (Tustison et al., TMI, 2010)
- Brain extraction using pyramidal intracranial masking (pincram)
  (cf. Heckemann et al., “DISPATCH”, MICCAI 2012 Grand Challenge on Multi-atlas Labeling, 2012)

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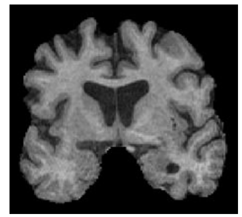
(ADNI1/2)



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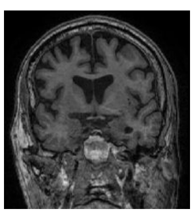
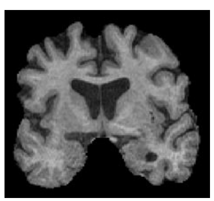
(CAAD data)





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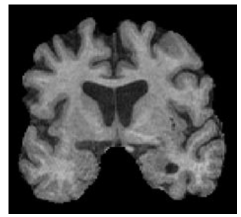

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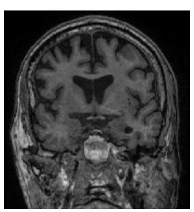
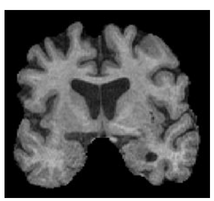
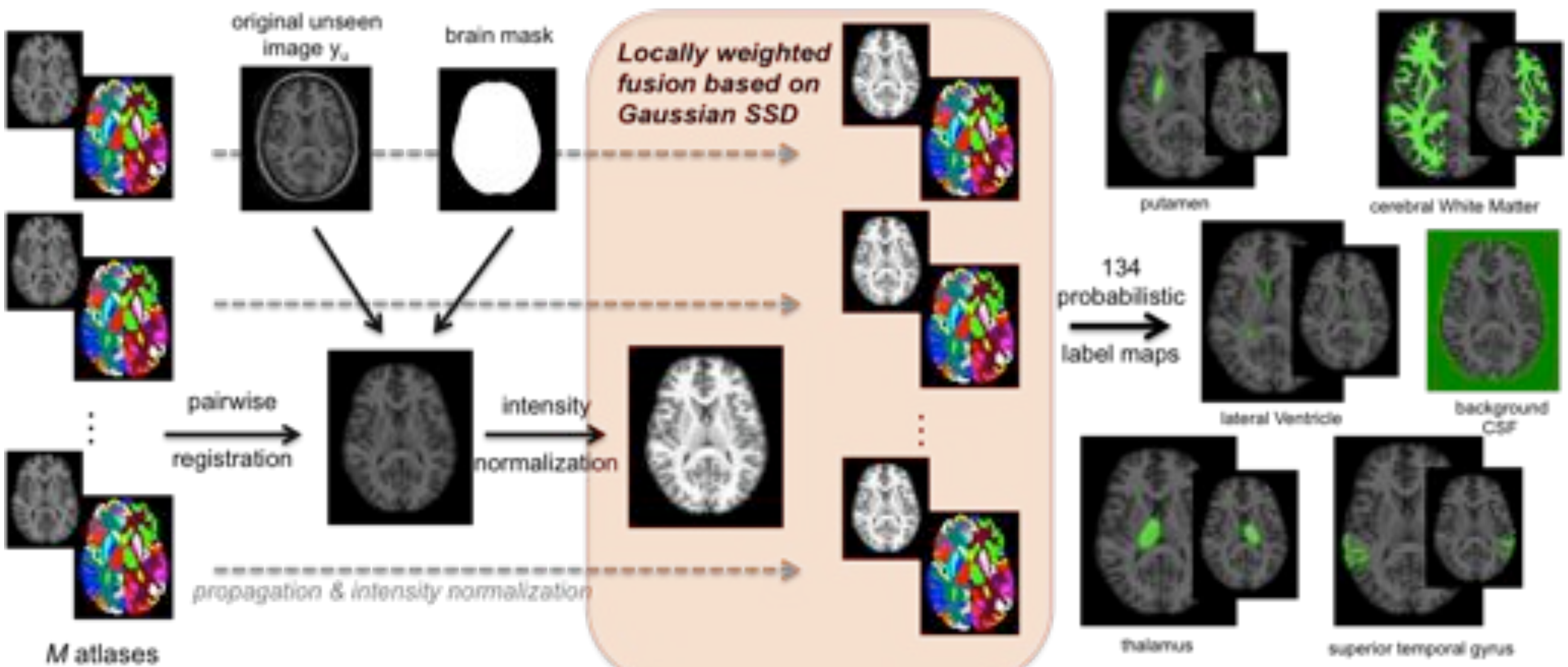




Whole-brain segmentation (MALP-EM)



(30 atlases provided by neuromorphometrics.com)

Ledig, C. et al., Multi-class brain segmentation using atlas propagation and EM-based refinement, ISBI 2012
Ledig, C. et al., Segmentation of MRI brain scans using MALP-EM, MICCAI Grand Challenge and Workshop on Multi-atlas labeling, 2012

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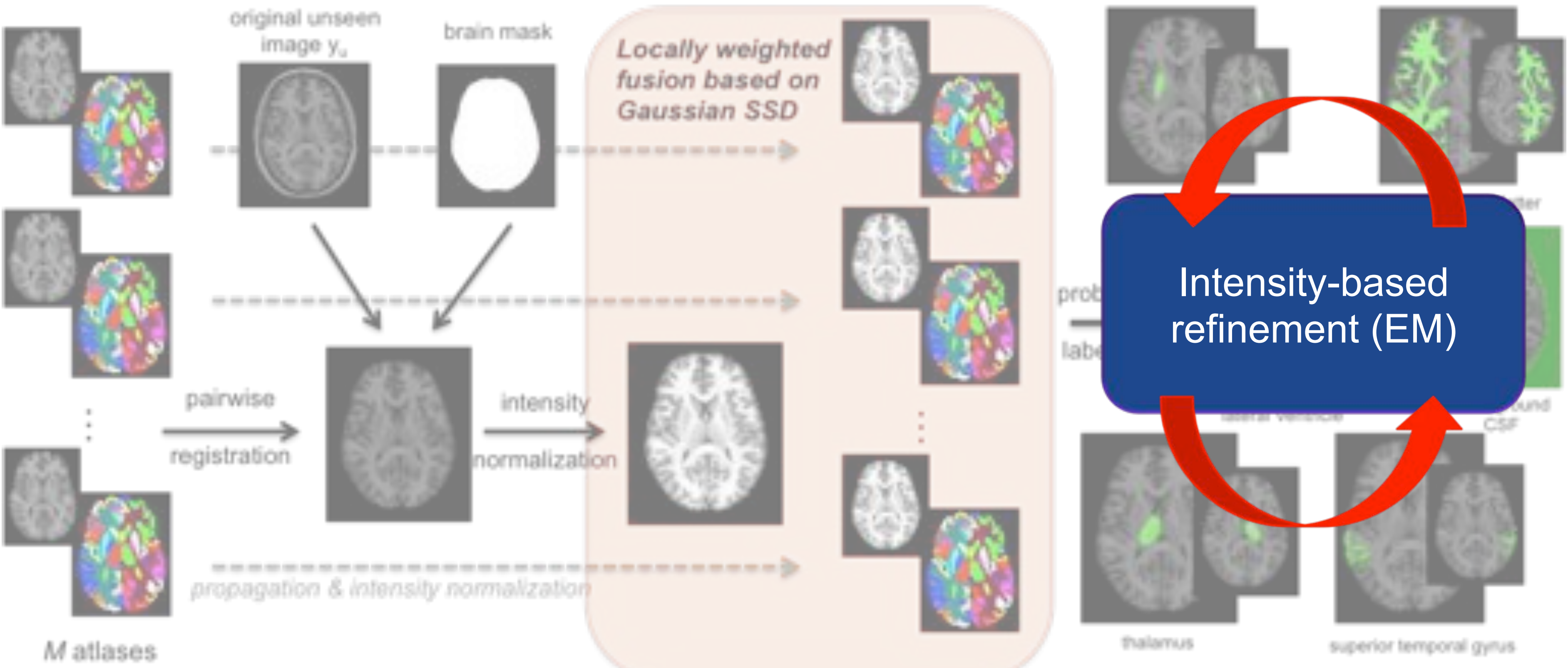

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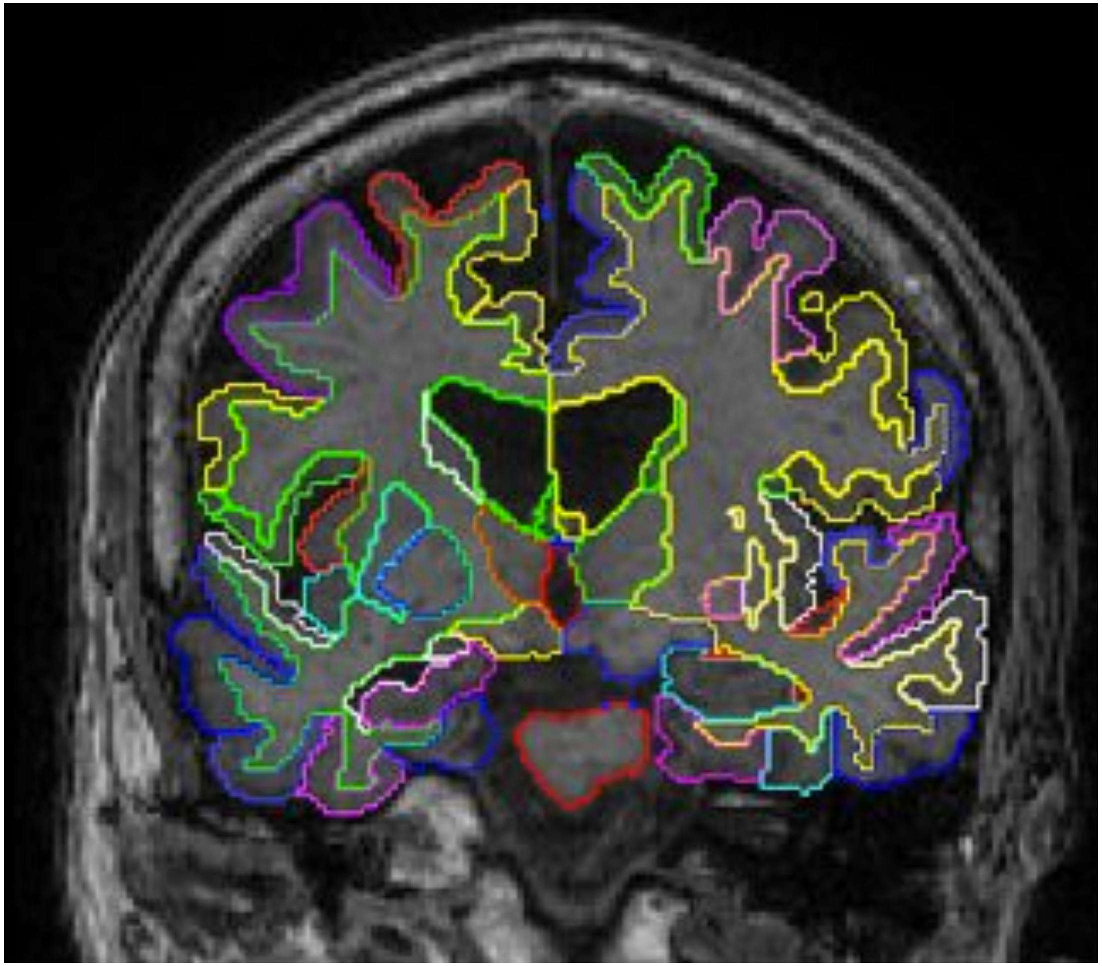

test_emc_051

structural volumes (VOL),
cortical thickness*/
cortical surface** (CORT)*

*S. E. Jones, et al., “Three-dimensional mapping of cortical thickness using laplace’s equation,” Human Brain Mapping, 2000.
**C. E. Rodriguez-Carranza, et al., “A framework for in vivo quantification of regional brain folding in premature neonates,” NeuroImage, 2008.

Overview

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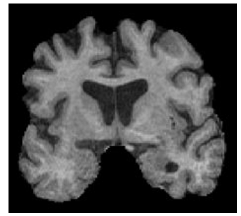
(ADNI1/2)



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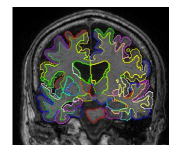
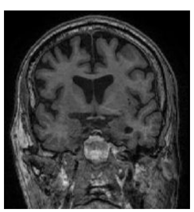
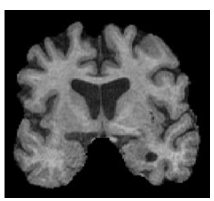


Manifold-based learning

Preprocessing
(CAAD data)

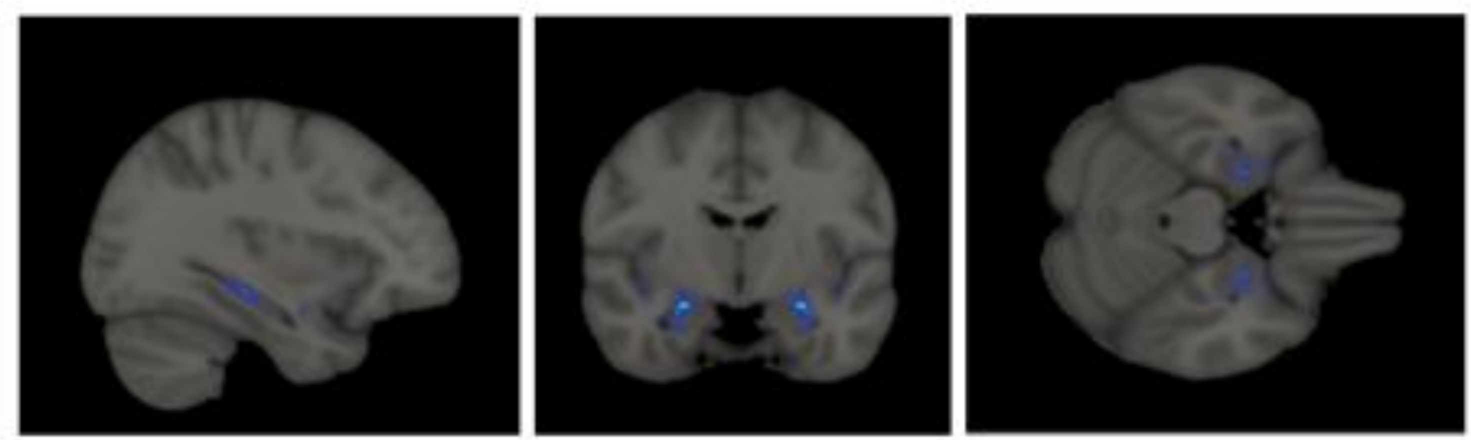




Manifold-based learning features (MBL)

(based on Guerrero et al. NeuroImage 2014)

- Learn ROI in template space using elastic net regression



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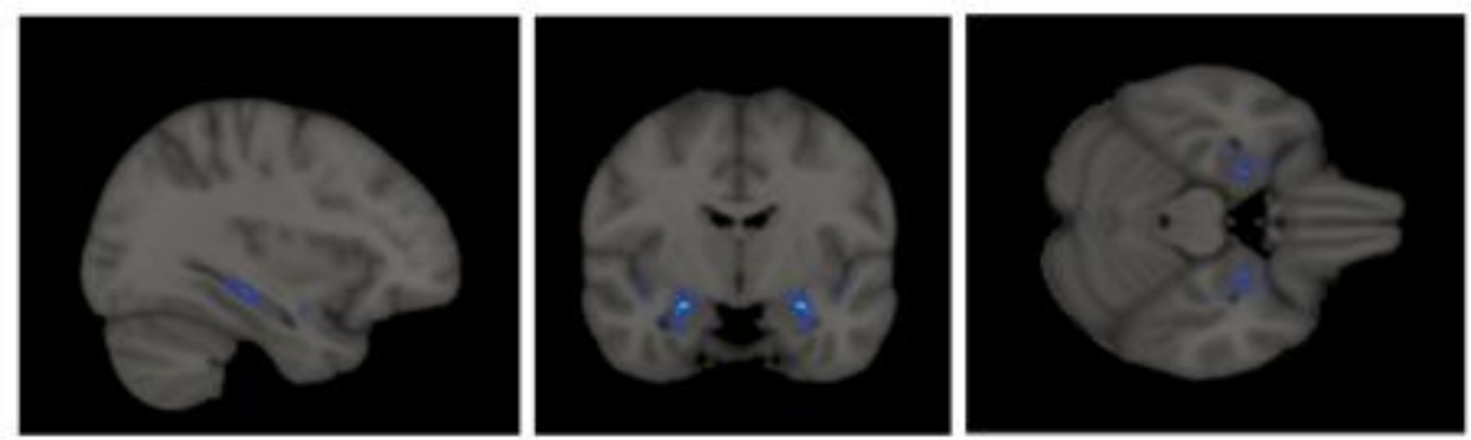
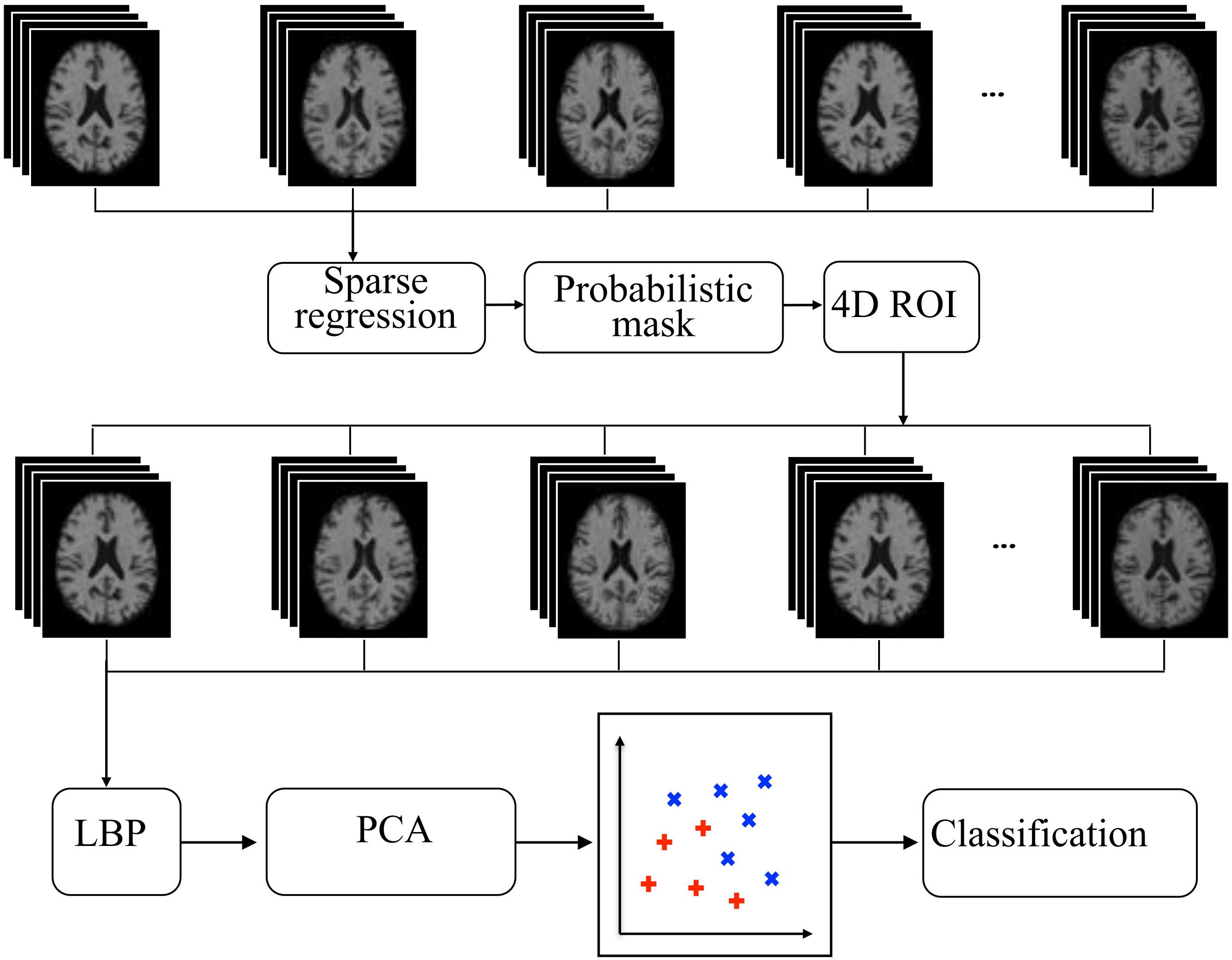


- Extract local binary patterns (LBP) from ROI of unseen images
- Reduce dimensionality (PCA)

Method Overview



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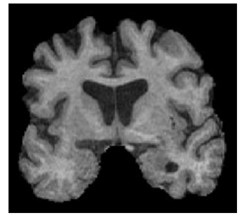
(ADNI1/2)



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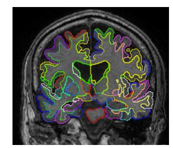

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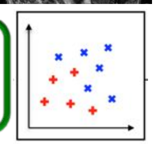
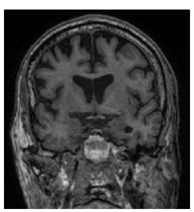
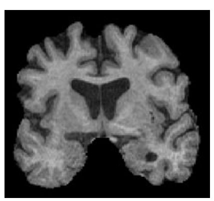


Patch-based grading

Preprocessing
(CAAD data)

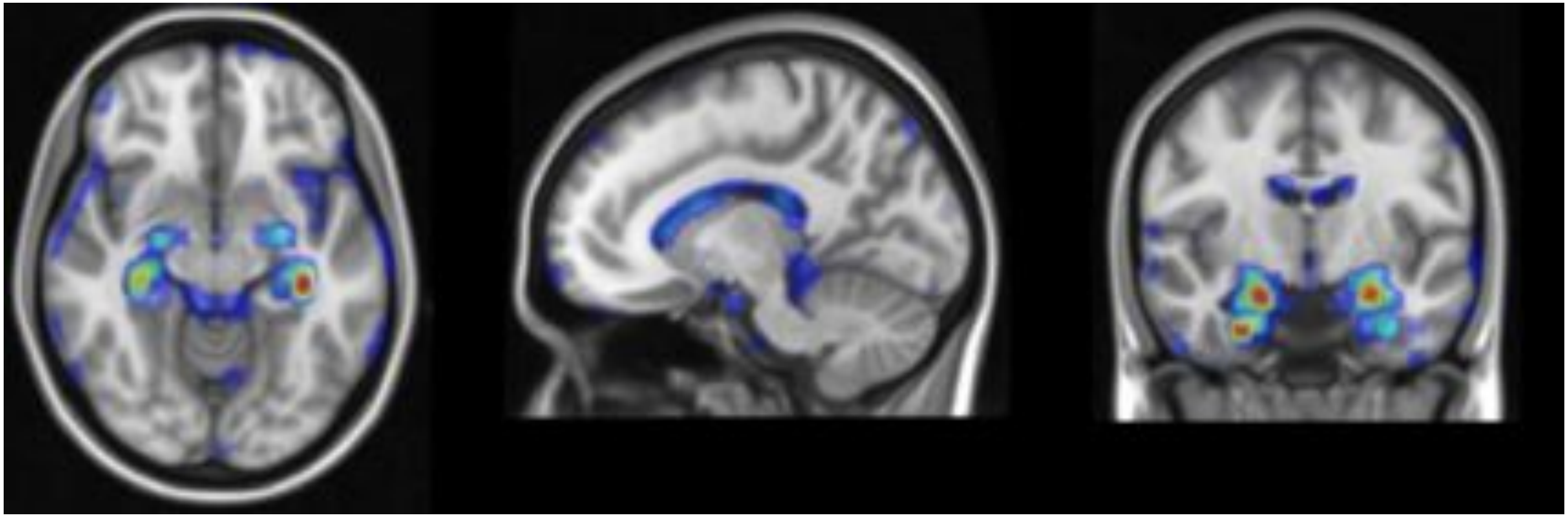




Patch-based grading features (GRAD)

(based on Tong et al. Medical Image Analysis 2014)

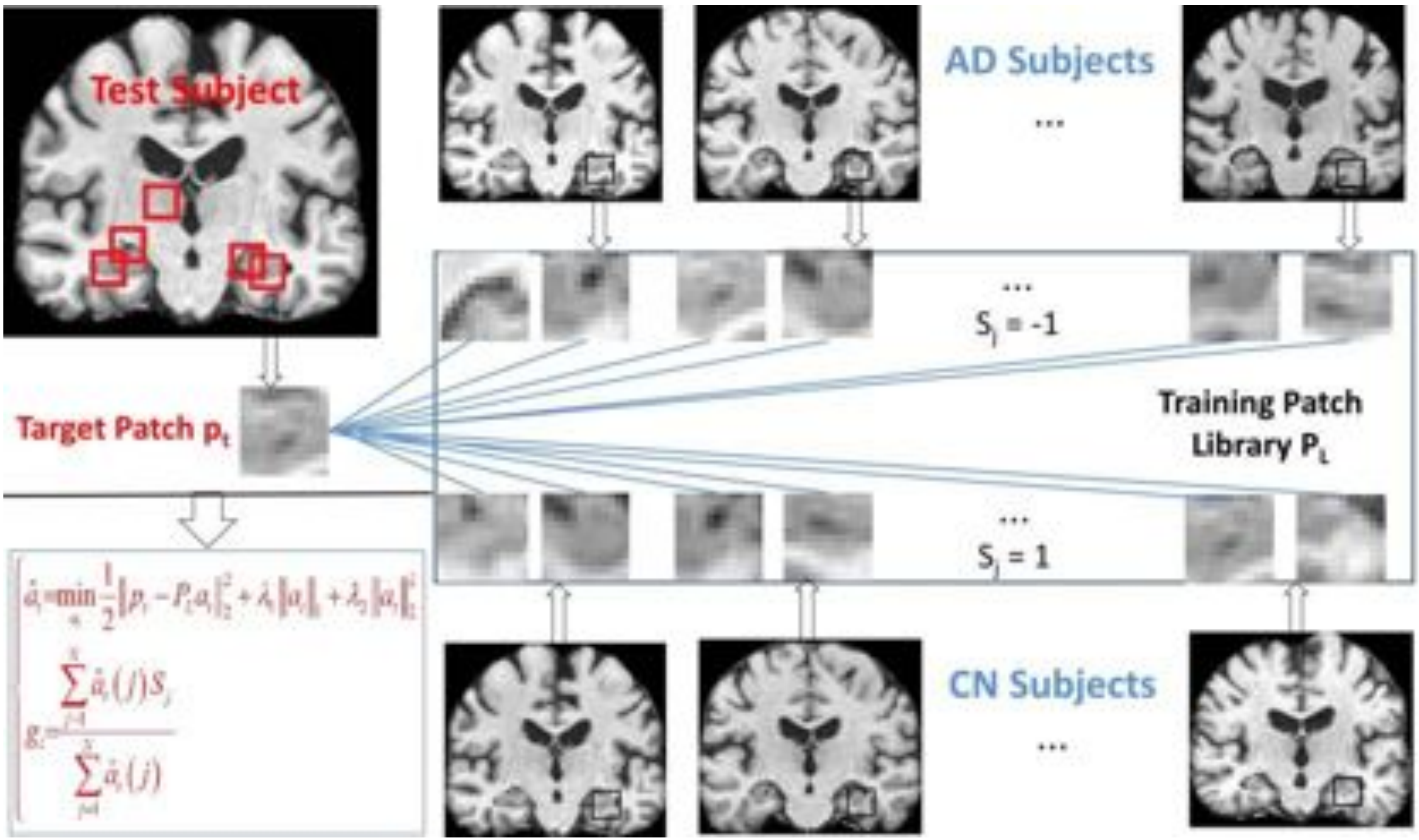
- **Extraction of Important Patches**
  - Generating probability map using Elastic Net (Guerrero et al., 2014)
  - Extracting patches at locations where pathological changes of AD might exist (i.e. high probability in the map). (Tong et al., 2014)



Probability maps for extracting important patches

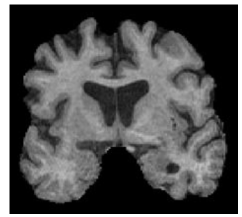
Grading Features Extraction

- **Compute Grading Features:**

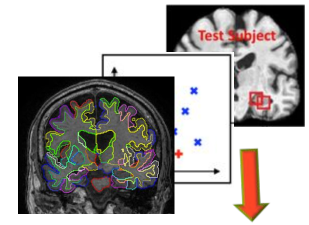


Classification using Random Forests

Training Data
(ADNI1/2)



Feature extraction



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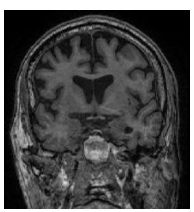

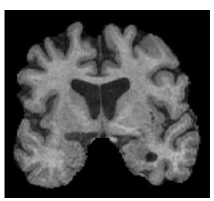

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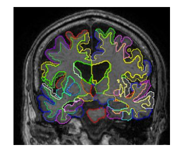
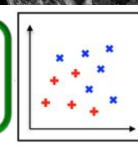
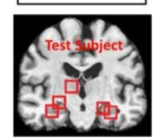
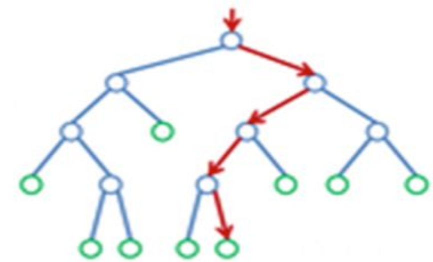


Manifold-based learning



Patch-based grading

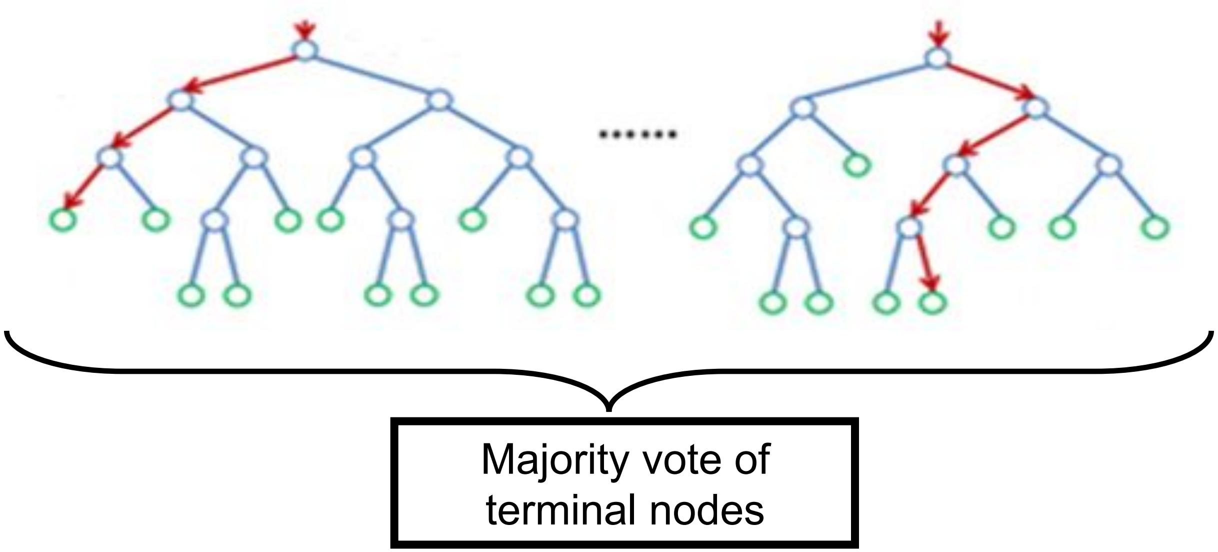




Healthy/MCI/AD?

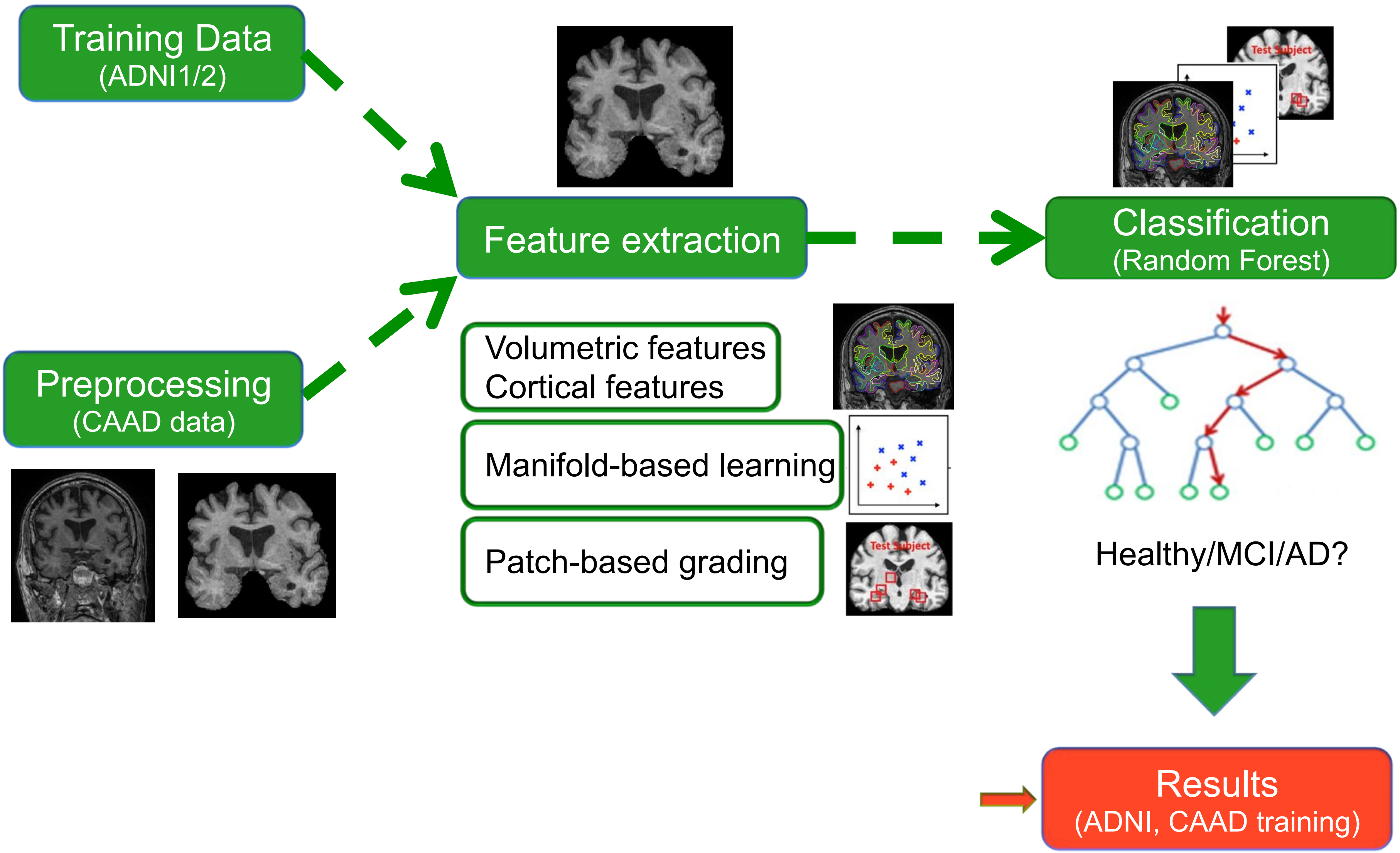
Random forest classifiers

- **Ensemble** of decision trees with rules for:
  - Training 100 trees
    - objects sampled at random with replacement to form tree-specific training set
    - At each tree node, randomly select variables to optimise binary split
  - Combining trees
    - Test data classified by simple majority voting across all trees in forest
  - Scikit-learn implementation (http://scikit-learn.org/)



Breiman, L., “Random Forests”, Machine Learning, 45(1), pp. 5-32

Experimental Results



Performance on ADNI cohorts

Table 2: Overview of the classification results for the 10-fold cross validation on the subset of the ADNI1-2 cohort. Mean classification accuracy (± SD) based on 10-fold cross validation.

Type	# Feat.	AD vs. CN	AD vs. MCI	MCI vs. HC	AD vs. MCI vs. HC
VOL	135	0.83±0.05	0.68±0.04	0.67±0.05	0.54±0.04
CORT	591	0.80±0.05	0.65±0.06	0.63±0.04	0.51±0.05
MBL	20	0.89±0.05	0.67±0.07	0.70±0.05	0.58±0.03
GRAD	150	0.86±0.04	0.67±0.04	0.69±0.04	0.56±0.04
ALL	896	0.87±0.03	0.68±0.04	0.72±0.05	0.59±0.04

best individual method

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best individual method

best overall

Performance on CADD training set

Table 3: Overview of the classification results obtained on CADDementia training data. Mean classification accuracy (± SD) based on 10 classification runs.

Type	# Feat.	AD vs. CN	AD vs. MCI	MCI vs. HC	AD vs. MCI vs. HC
VOL	135	0.86±0.03	0.73±0.05	0.68±0.05	0.56±0.08
CORT	591	0.91±0.05	0.67±0.09	0.65±0.05	0.58±0.07
MBL	20	0.94±0.02	0.62±0.04	0.75±0.04	0.66±0.01
GRAD	150	0.88±0.03	0.75±0.06	0.76±0.03	0.67±0.05
ALL	896	0.92±0.02	0.78±0.05	0.75±0.04	0.68±0.05

best individual method

best overall

Computation Times

Table 4: Overview of the approximate computation times per subject.

Task	Runtime	Implementation	Automatic
N4 bias correction	$<$ 30 minutes	single core	yes
pincram brain extraction	$<$ 1 hour	parallel	yes*
registration of the 30 atlases (VOL)	$<$ 2 hours	parallel	yes
atlas fusion (VOL)	$<$ 20 minutes	single core	yes
cortical thickness (CORT)	$<$ 15 minutes	single core	yes
local binary patterns (MBL)	$<$ 1 second	single core	yes
dimensionality reduction, $\sim$1800 subjects (MBL)	$<$ 10 seconds	parallel	yes
Grading feature extraction (GRAD)	$<$ 5 minutes	single core	yes
classification	$<$ 1 second	single core	yes

*(manual quality control)

Conclusion

- All our methods are fully automatic
  - exception: The visual quality check of brain masks
- The more involved manifold learning and patch-based methods outperform the rather simple structural analysis
- Little complementary information between feature sets
- Substantially higher classification accuracies on challenge data than on ADNI
  - but: small sample size (N=30)
  - suggests higher quality data and/or clearer group separation of patient groups

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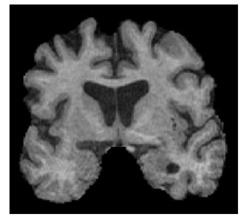

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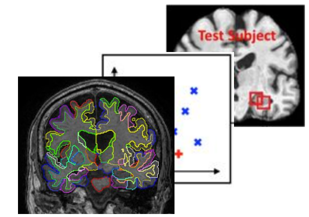

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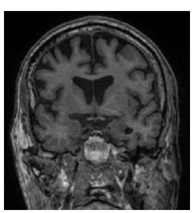

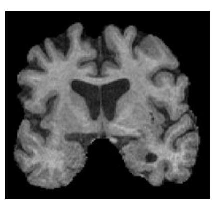

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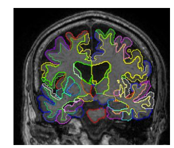
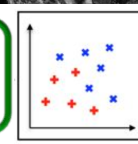


Manifold-based learning



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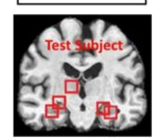

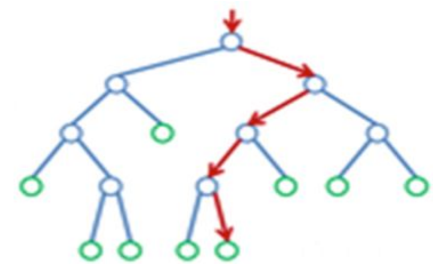

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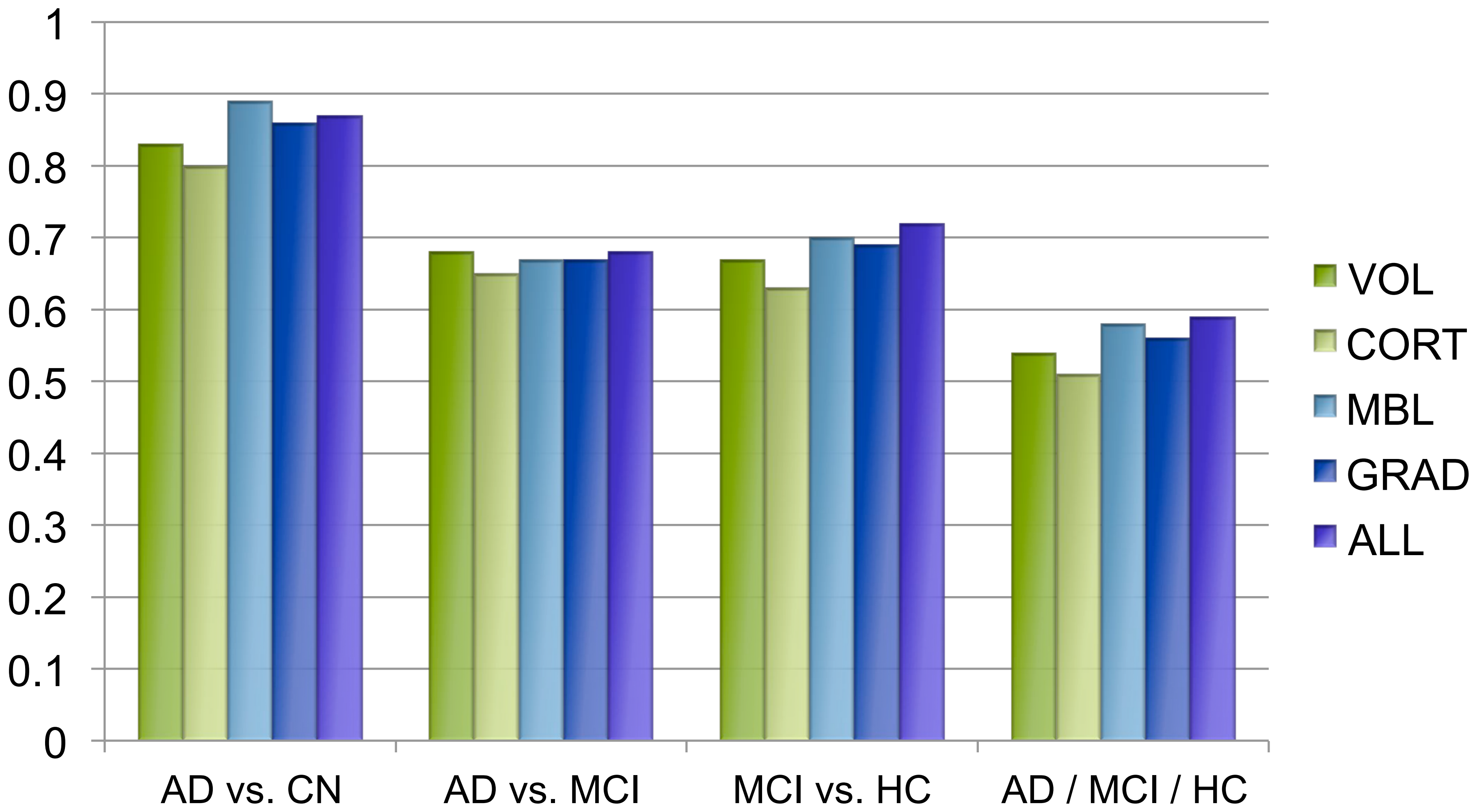

Performance on CADD training set