Characterizing Neural Signatures of Dyslexia and Co-occurring Math Learning Difficulties (MLD) with Machine Learning

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Introduction

- 10% of children face persistent learning difficulties in reading and math, the most common is developmental dyslexia (DD) among which 40% concurrently experience math learning difficulties (MLD)
- Previous machine learning studies have focused on the distinction between children with dyslexia and typically developing controls, without regard for math learning difficulties
- Objective: Classify children with dyslexia and/or MLD using brain deviation scores produced from large-scale normative modeling

Methods

Study Population: UCSF Dyslexia Center participants (N=300) received extensive neuropsychological evaluations (15+ hrs) in reading and math by interdisciplinary team

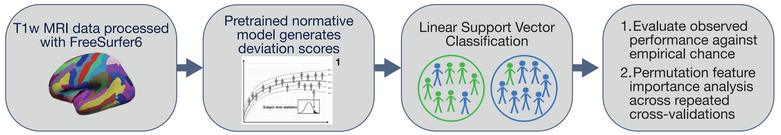
Sample Characteristics (N = 300)			
	DD & MLD (N = 115)	DD Only (N = 136)	MLD Only (N = 49)
Age mean (SD) range	11.49 (2.05) 8 - 17	10.75 (2.30) 7 - 17	11.63 (2.15) 7 - 15
Sex: male N (%)	65 (56.52%)	76 (55.88%)	23 (46.94%)

Data Preprocessing

- Open source pretrained warped bayesian linear regression normative models **(82 sites; N=58,536; ages 2-100)**[1] to generate brain deviation scores which account for: age, sex, and MRI site effects
  - Measures: cortical area and thickness (Destrieux atlas[2]) and subcortical volume (Aseg atlas[3])

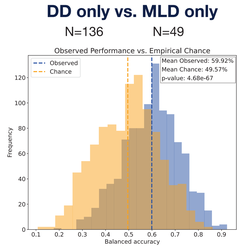
Binary Classification

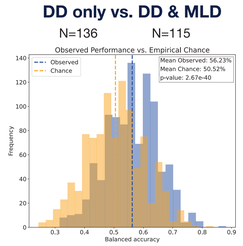
- Class groupings: DD only vs. MLD only; DD only vs. DD & MLD; MLD only vs. DD & MLD
- Features: Deviation scores for pre-defined math[4] and language[5] brain regions (N=64) selected based on meta-analyses
- Model: Linear support vector classification; hyperparameters optimized with grid search (l2 penalty, hinge loss function); 10-fold cross validation repeated 100x

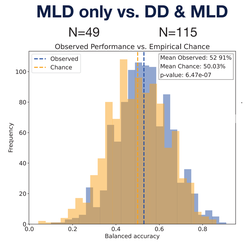


Results

Observed Performance vs. Empirical Chance

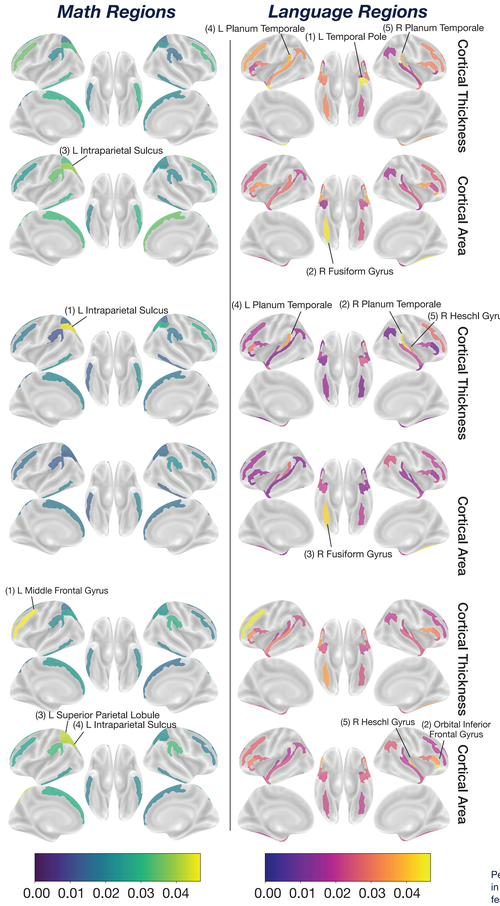




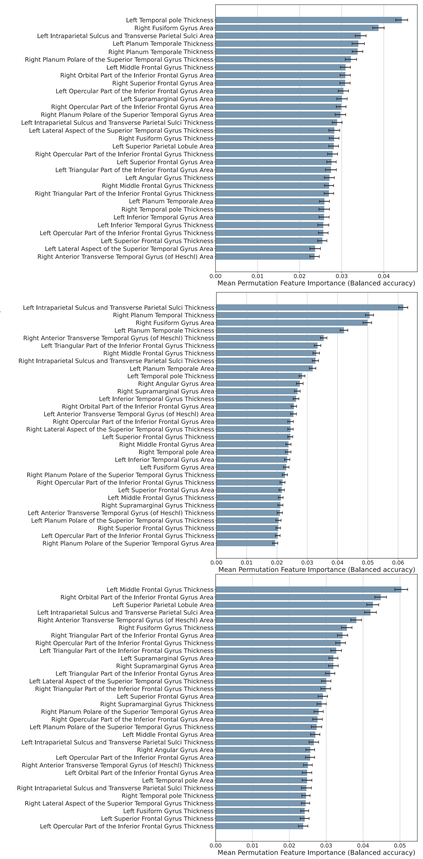


Classification model was run with 10-fold cross validation 100 times (randomized CV split for each repeat) with true labels and then again with shuffled labels to produce an empirical chance comparison to the observed performance. Performance metric was balanced accuracy ((sensitivity + specificity)/2).

Mean Permutation Feature Importance



Top Features Ranked by Mean Permutation Feature Importance



Permutation feature importance (PFI) was calculated by permuting individual features 100 times, in each fold of 10-fold CV repeated 100 times, totaling 100,000 datapoints for the effect of a given feature on the model. Feature contribution measured by the mean and standard error of PFI.

Conclusions

- **DD only vs. MLD only** ✓
  - Balanced Accuracy: 60%
  - Top features: (1) L temporal pole, (2) R fusiform gyrus, (3) L intraparietal sulcus (IPS), (4) L planum temporale, and (5) R planum temporale
  - Abnormalities mainly along the **temporal language regions**
- **DD only vs. DD & MLD** ✓
  - Balanced Accuracy: 56%
  - Top features: (1) L intraparietal sulcus, (2) R planum temporale, (3) R fusiform gyrus, (4) L planum temporale, (5) R heschl gyrus
  - Abnormalities in **parietal math** and **temporal language regions**
- **MLD only vs. DD & MLD** ✗
  - Balanced Accuracy: 53%
  - Top features: (1) L middle frontal gyrus, (2) R orbital inferior frontal gyrus, (3), L superior parietal lobule, (4) intraparietal sulcus, (5) R heschl gyrus
  - Abnormalities in **executive regions**; larger difference in prevalence of dysexecutive symptoms (22% vs. 50%)*

*Proportion of Children with Dysexecutive Symptoms: DD only: 0.34, DD & MLD: 0.50, MLD only: 0.22

Acknowledgements

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