Exploring the Efficacy of Machine Learning Integrating DTI Biomarkers and Classification Techniques to Facilitate Timely Detection and Precise Stratification of Discrete Stages in Alzheimer's Disease BOSTON

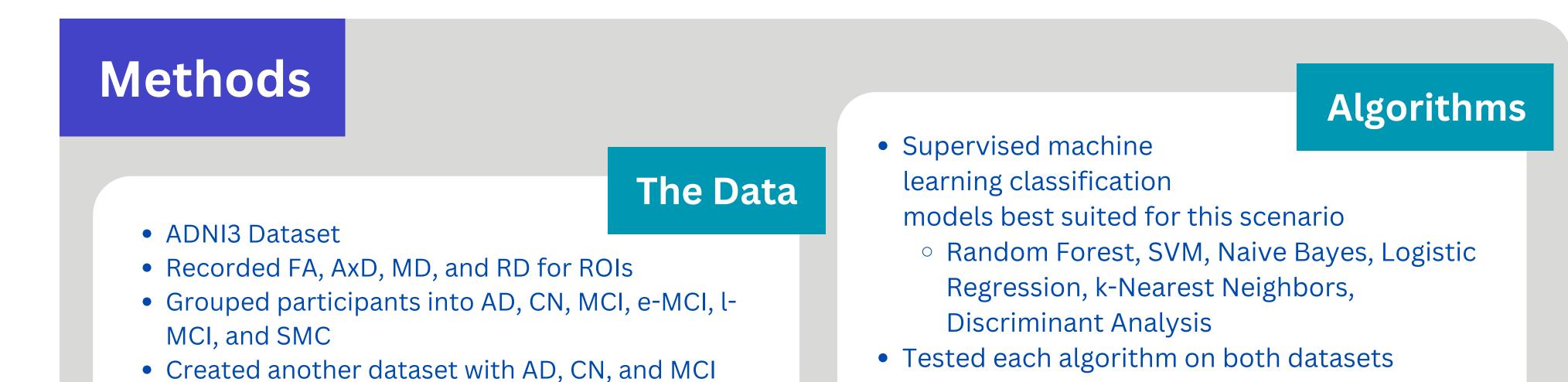
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# **Background & Aims**

**Background.** Alzheimer's Disease (AD) leads to a reduction in white matter volume, especially in the medial temporal and hippocampal regions<sup>1</sup>

• DTI is a neuroimaging technique sensitive to microscopic changes of brain tissue, making it a vital tool for detecting early changes in brain structure before the onset of severe symptoms<sup>2</sup>



• Used metrics of accuracy, precision, recall, and F-score to evaluate performance

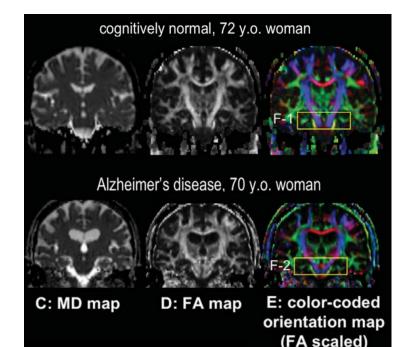
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• Early detection is of utmost importance for timely treatment and prevention of further cognitive deterioration<sup>3</sup>

**Aims.** Classify patients as having AD, Mild Cognitive Impairment (MCI), or normal cognition based on various DTI measures of ROIs and identify significant biomarkers in prediction. • Additionally, identify which DTI measure is most significant



- Removed confounding variables
- Standardized data using StandardScaler
- Principal Component Analysis



• Created confusion matrices to evaluate performance for each research group

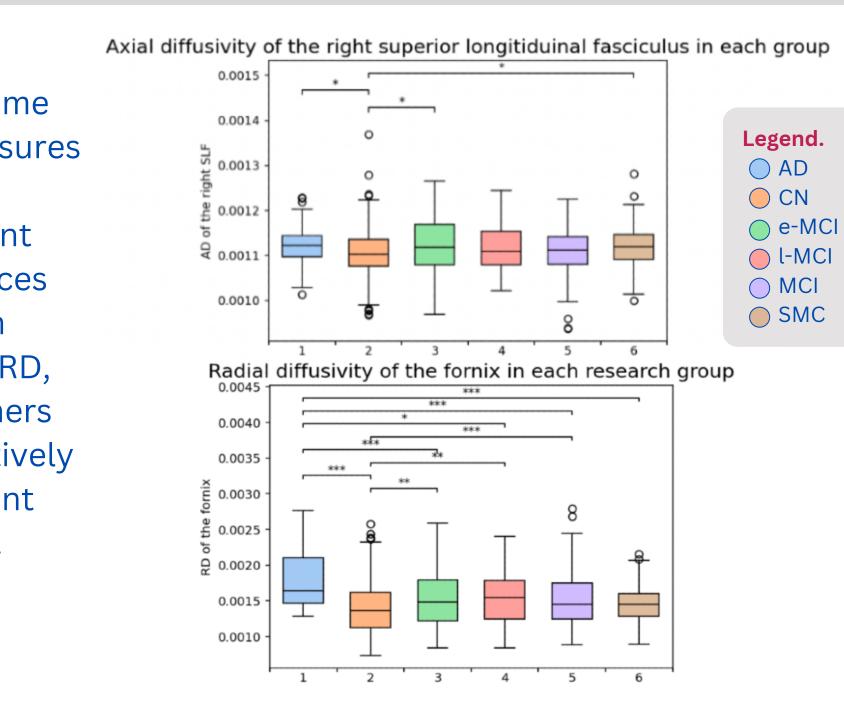
#### Resampling

• Imbalance of samples across research groups = biased models • Tested both oversampling and undersampling techniques to balance • bSMOTE, ADASYN, ENN, etc.

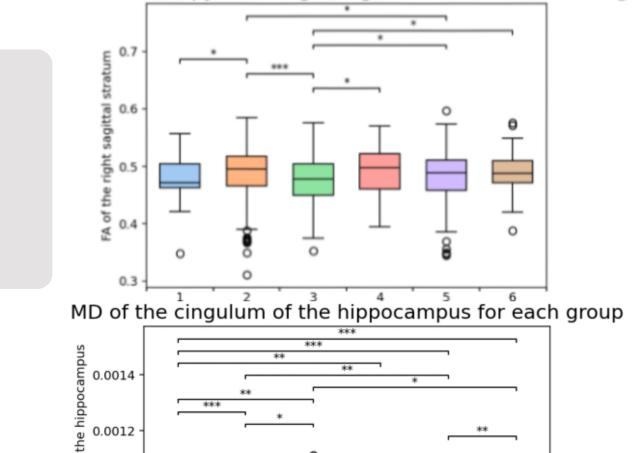
### Results

<b>Fig. 1.</b> The top 9 features of the Random	Brain Structure	DTI Measure										
	Hippocampal cingulum - left (CGH-L)	MD										
	Body of corpus callosum (BCC)	AD										
	Hippocampal cingulum - left (CGH-L)	RD										
Forest Classification	Fornix/stria terminalis (FXST)	MD										
algorith,	Fornix (FX)	RD										
sorted by	Corticospinal tract - right (CST-R)	FA										
brain structure,	Fornix (FX)	FA										
DTI measure,	Sagittal stratum - right (SS-R)	FA										
and importance.	Superior fronto-occipital fasciculus - left	AD										
	* Higher importance numbers correlate to higher significance											

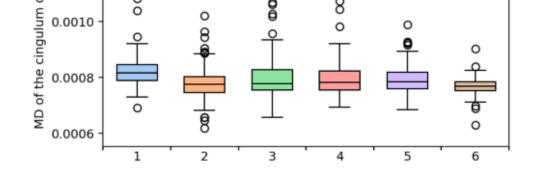
	<b>Fig. 2.</b> While some
	DTI measure
	show
Importance	significant
0.02235	differences
0.0164	between
0.0104	groups (RD,
0.01556	MD), others
0.01384	are relatively
0.01233	consistent











• When examining different algorithms, it's important to consider a variety of metrics • While some models have a high overall accuracy score, that may be because they are biased towards a certain group

<b>Fig. 3.</b> Each confusion matrix and		L	AD CN MCI MCI MCI SMC	ecision 0.79 0.85 0.78 0.72 0.65 0.76	0. 0. 0.	99 13 77 95 72 94	-score 0.88 0.23 0.77 0.82 0.68 0.84	support 158 171 171 157 161 157		EM LM S	AD CN ICI ICI ICI IMC	ecision 0.98 0.84 0.93 0.99 0.87 0.93	recal 0.9 0.7 0.9 0.9 0.9 0.9	7 4 5 8 0	-score 0.98 0.79 0.94 0.99 0.88 0.96	support 176 149 145 176 166 163		EM LM S	AD CN ICI ICI ICI ICI	ecision 0.96 0.86 0.93 0.98 0.83 0.83 0.97	recal 0.9 0.7 0.9 0.9 0.9 0.9	0.8 0.9 0.8 0.8	96 30 94 98 36 98	support 150 160 157 167 171 170
classification report represents the three	we	accur macro ighted	avg	0.76 0.76		75 74	0.74 0.70 0.70	975 975 975		accura macro a ghted a	vg	0.92 0.93	0.9 0.9		0.93 0.92 0.93	975 975 975		accura macro a ghted a	vg	0.92 0.92	0.92 0.92		92	975 975 975
best-performing	0 -	0.99	0.00	0.00	0.00	0.01	0.00		0	- 0.97	0.02	0.00	0.00	0.01	0.00		o -	0.97	0.00	0.00	0.01	0.03 0	0.00	
models k-Nearest Neighbors,		0.10	0.13	0.16	0.16	0.28	0.16	- 0.8	1	- 0.00	0.74	0.03	0.01	0.13	0.07	- 0.8	1 -	0.03	0.75	0.05	0.01	0.12 0	.04	- 0.8
Gradient Boosting, and Random Forest)	tual 2	0.07	0.02	0.77	0.08	0.05	0.01	- 0.6	ctual 2	- 0.01	0.03	0.95	0.00	0.00	0.00	- 0.6	ctual 2	0.00	0.03	0.96	0.00	0.02 0	.00	- 0.6
from left to right.	3 Ac	0.01	0.00	0.01	0.95	0.01	0.03	- 0.4	Υ Ψ	- 0.00	0.00	0.01	0.98	0.01	0.00	- 0.4	3 Ac	0.00	0.00	0.01	0.98	0.01 0	.00	- 0.4
	4 -	0.07	0.01	0.04	0.08	0.72	0.09	- 0.2	4	- 0.01	0.07	0.02	0.00	0.90	0.01	- 0.2	4 -	0.01	0.09	0.01	0.01	0.88 0	0.00	- 0.2
	Ω -	0.01	0.00	0.01	0.02	0.03	0.94		ŝ	- 0.00	0.01	0.00	0.00	0.00	0.99	- 0.0	ι <b>υ</b> -	0.01	0.00	0.00	0.00	0.01 0	.99	-0.0
		0	1	2 Prec	3 licted	4	5	- 0.0		ò	i	2 Pred	3 cted	4	5	0.0	0 1 2 3 4 Predicted					4	5	

0.01217

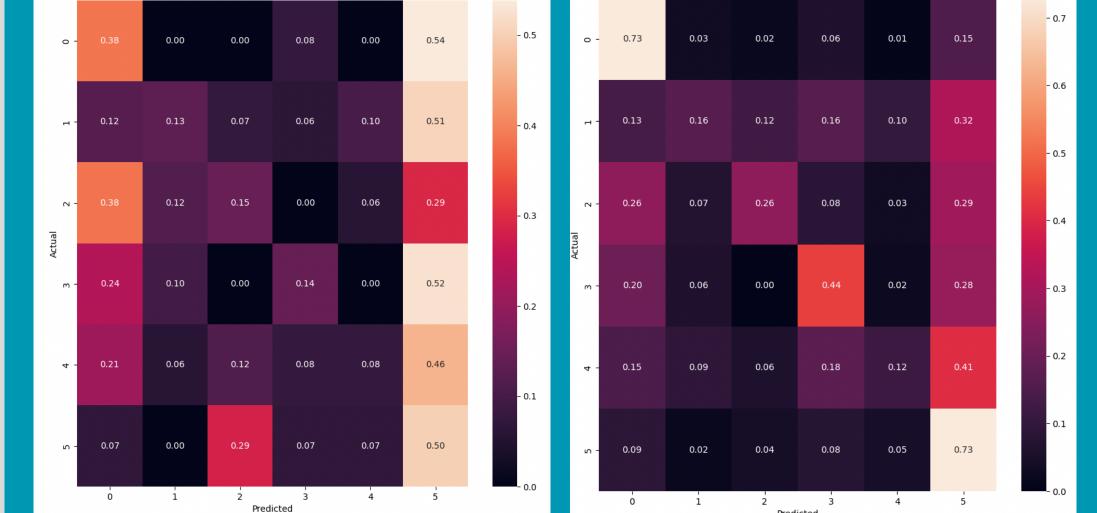
0.01135

0.00993

0.00845

#### Before and After Resampling (bSMOTE)





## Discussion

Analyzing results. Using a Gradient Boosting Algorithm with SMOTE + ENN produces best average accuracy score

- However, accuracy for predicting CN is extremely low --> bSMOTE is preferred
- AD first damages the entorhinal cortex, aligns with our findings of significant ROIs in prediction<sup>4</sup>

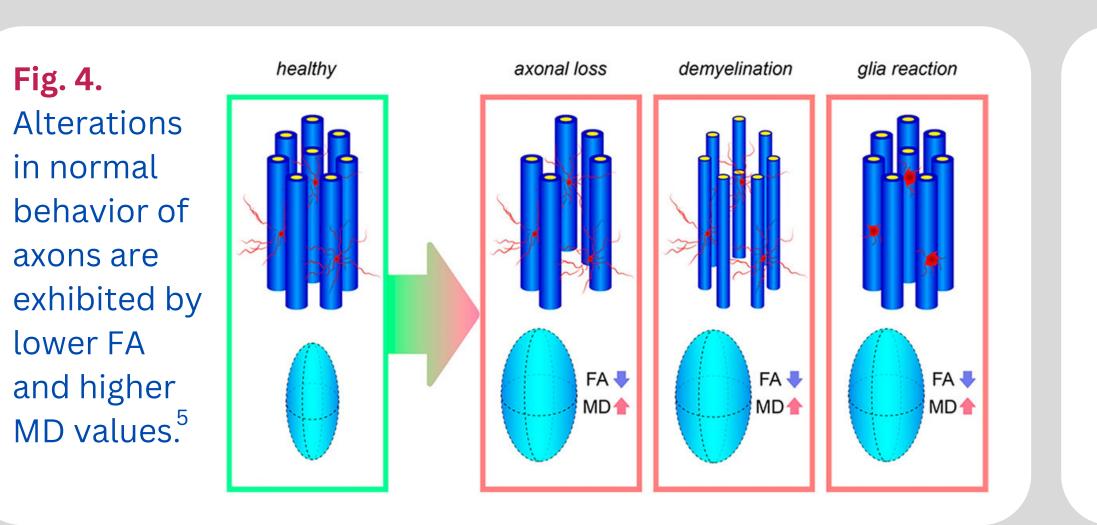


Fig. 5. Significant ROIs, from left to right and top to bottom, are as follows: sagittal stratum, cingulum of the hippocampus, fornix stria terminalis, fornix

References. [1] Kao YH, Chou MC, Chen CH, Yang YH. White Matter Changes in Patients with Alzheimer's Disease and Associated Factors. J Clin Med. 2019;8(2):167. Published 2019 Feb 1. doi:10.3390/jcm8020167 [2] Nir TM, Jahanshad N, Villalon-Reina JE, et al. Effectiveness of regional DTI measures in distinguishing Alzheimer's Disease, MCI, and normal aging. Neuroimage Clin. 2013;3:180-195. Published 2013 Jul 27. doi:10.1016/j.nicl.2013.07.006 [3] Rasmussen J, Langerman H. Alzheimer's Disease - Why We Need Early Diagnosis. Degener Neurol Neuromuscul Dis. 2019;9:123-130. Published 2019 Dec 24. doi:10.2147/DNND.S228939 [4] Raji CA, Lopez OL, Kuller LH, Carmichael OT, Becker JT. Age, Alzheimer disease, and brain structure. Neurology. 2009;73(22):1899-1905. doi:10.1212/WNL.0b013e3181c3f293 [5] Silvia De Santis, Wolfgang H. Sommer, and Santiago Canals Detecting Alcohol-Induced Brain Damage Noninvasively Using Diffusion Tensor Imaging ACS Chemical Neuroscience 2019 10 (10), 4187-4189 DOI: 10.1021/acschemneuro.9b00481 Acknowledgements. I would like to thank my RA, Owen Borders, and my mentor, Professor Lipeng Ning, for guiding me through this project, as well as the Psychiatry Neuroimaging Laboratory for providing valuable instruction in computational neurobiology. Special thanks to the Boston University RISE program and my family for making this experience possible.