TO WHAT EXTENT MRI ACQUISITION PARAMETER LEADS TO ACQUISITION SHIFT?

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SECTION 1

BACKGROUND

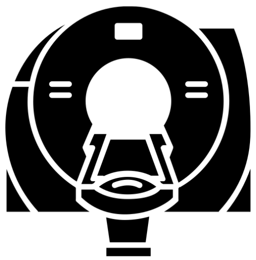
MACHINE LEARNING IN MEDICAL IMAGING

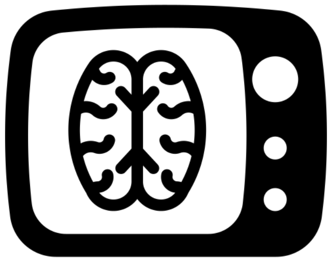
Predict Alzheimer's conversion from MR images

Machine learning framework for early MRI-based Alzheimer's conversion prediction in MCI subjects (Moradi et al., 2015)

Predict Parkinson's disease from MR images

Machine learning on brain MRI data for differential diagnosis of Parkinson's disease and Progressive Supranuclear Palsy(Salvatore et al., 2014)





CAUSALITY MATTERS IN MEDICAL IMAGING

Causality matters in medical imaging (Castro et al., 2020) :

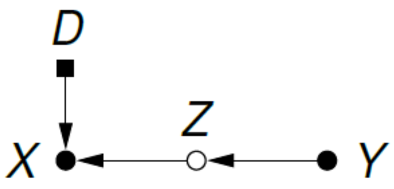
- Establishing a causal relationship between images and annotations will help researchers to identify potential biases and issues in advance;
- The paper offers step-by-step recommendations.

Table 4 Step-by-step recommendations

1. Gather meta-information about the data collection and annotation processes to reconstruct the full story of the dataset (Table 1).
2. Establish the predictive causal direction: does the image cause the prediction target or vice versa?
3. Identify any evidence of mismatch between datasets (Table 2):
   - If causal (image $\rightarrow$ target): population shift, annotation shift
   - If anticausal (target $\rightarrow$ image): prevalence shift, manifestation shift
4. Verify what types of differences in acquisition are expected, if any.
5. Determine whether the data collection was biased with respect to the population of interest, and whether selection was based on the images, the targets, or both (Table 3).
6. Draw the full causal diagram including postulated direction, shifts, and selections.

MOTIVATION

- Acquisition shift;
- What is acuiqisiton shift:



(Anticausal) Acquisition shift:
$\boldsymbol{P_D(X|Z)}P(Z|Y)P(Y)$

X is the acquired image;
Y, the prediction target;
Z, the unobserved true anatomy;
D, the domain indicator (different acquisition parameters).

- Why important: the classifier may learn a criterion based on the acquisition parameters rather than the medical condition.

RESEARCH PROBLEM

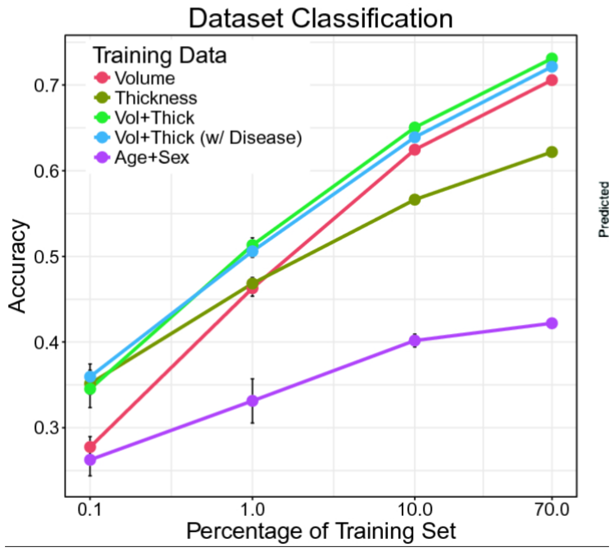
1. To what extent the causal analysis and the suggested step-by-step recommendation will make difference?
2. More specifically, we will mainly focus on acquisition shift. We will focus on the data mismatch due to different MRI acquisition parameters and investigate whether different MRI acquisition parameters can be detected by machine learning approaches.

RELATED WORK

- A study shows that the differences due to the acquisition protocol can have a strong impact on machine learning models[1].

	NYU_ABIDE1	OHSU_ABIDE1	...
NYU_ABIDE1	/	0.99±0.04	...
OHSU_ABIDE1		/	...
...	...	...	...

- Another study shows MRI scans from different datasets can be correctly assigned to their respective dataset with 73.3% accuracy[2].



[1] Common pitfalls in machine learning applications to multi-center data: tests on the ABIDE I and ABIDE II collections (Ferrari et al., 2018)
[2] Quantifying Confounding Bias in Neuroimaging Datasets with Causal Inference (Wachinger et al., 2019)

SCHWAB AND ENGLAND ADL SCALE

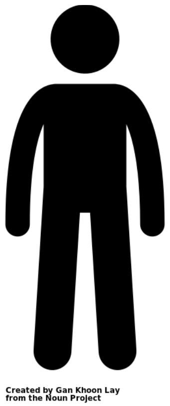
- Evaluate the different levels of severity of Parkinson's patients.

- Represent how much effort and dependence on others people need to complete daily chores.

- [0%, 100%].

- An alternative of MDS-UPDRS.

100%



0%

SECTION 2

DATASET & PREPROCESSING

DATASET - PPMI

Parkinson Progression Marker Initiative (PPMI): an international, multi-center study designed to identify PD (Parkinson's Disease) progression biomarkers

Total subjects:

- 797 diagnosed PD subjects
- 234 healthy control subjects

Data types:

- clinical
- imaging
- biospecimen biomarker assessment

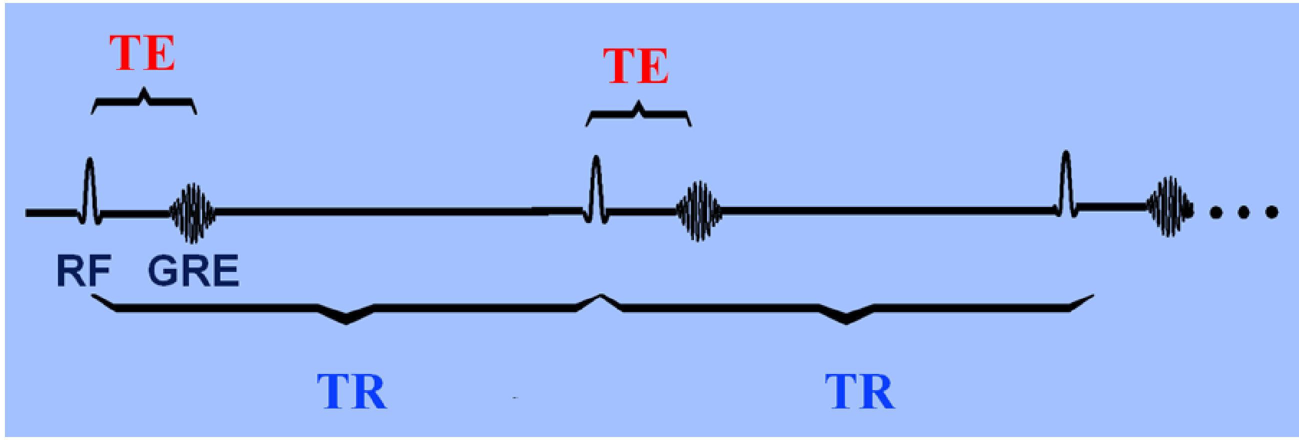
  metadata (sex, age, weight, acquisition settings...)

MRI

Magnetic resonance imaging (MRI): a medical imaging technique that uses a magnetic field and computer-generated radio waves to create detailed images of the organs and tissues.

Parameters:

1. **TE(Echo time)**: the time from the center of the RF-pulse to the center of the echo.
2. **TR(Repetition time)**: the length of time between corresponding consecutive points on a repeating series of pulses and echoes.
3. **TI(Inversion time)**: the time between the 180° inverting pulse and the 90°-pulse.

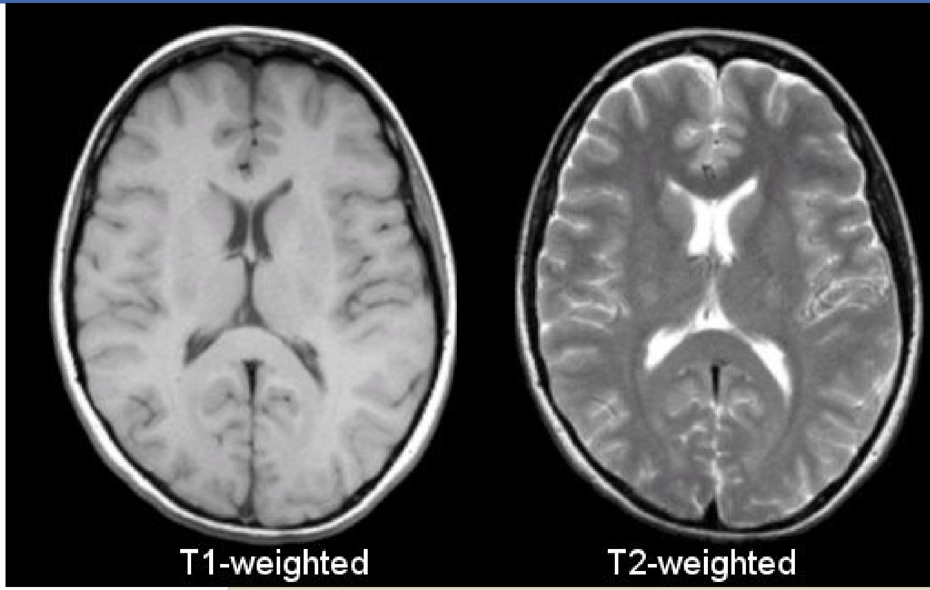


MRI

T1 vs T2:

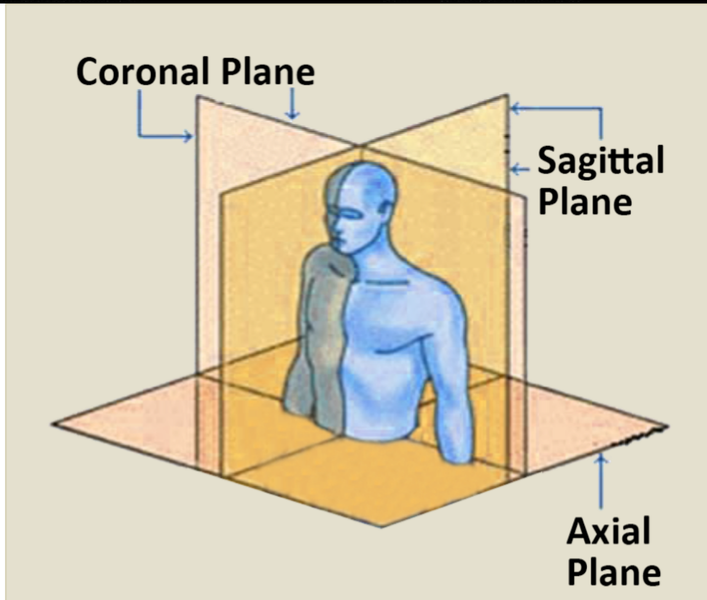
- T1: short TE and TR
- T2: long TE and TR

	T1	T2
CSF	dark	bright
White Matter	light	dark gray
Cortex	gray	light gray
Fat	bright	light
Inflammation	dark	bright

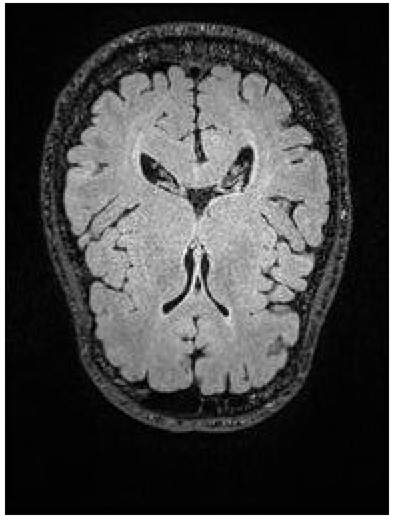


Acquisition Plane:

- sagittal
- axial
- coronal



PREPROCESSING PIPELINE

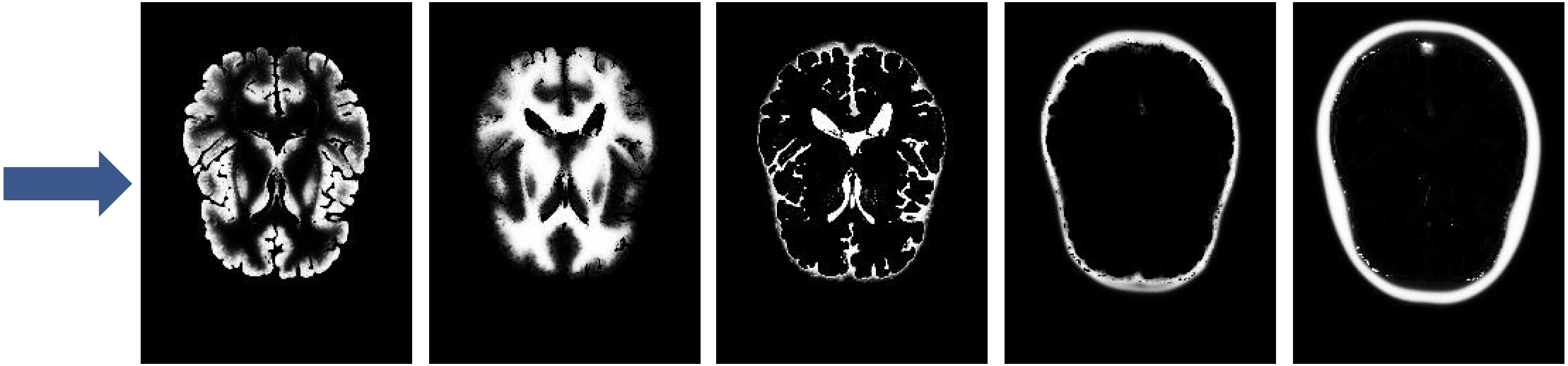


original image

skull stripping

bias field correction

PREPROCESSING PIPELINE

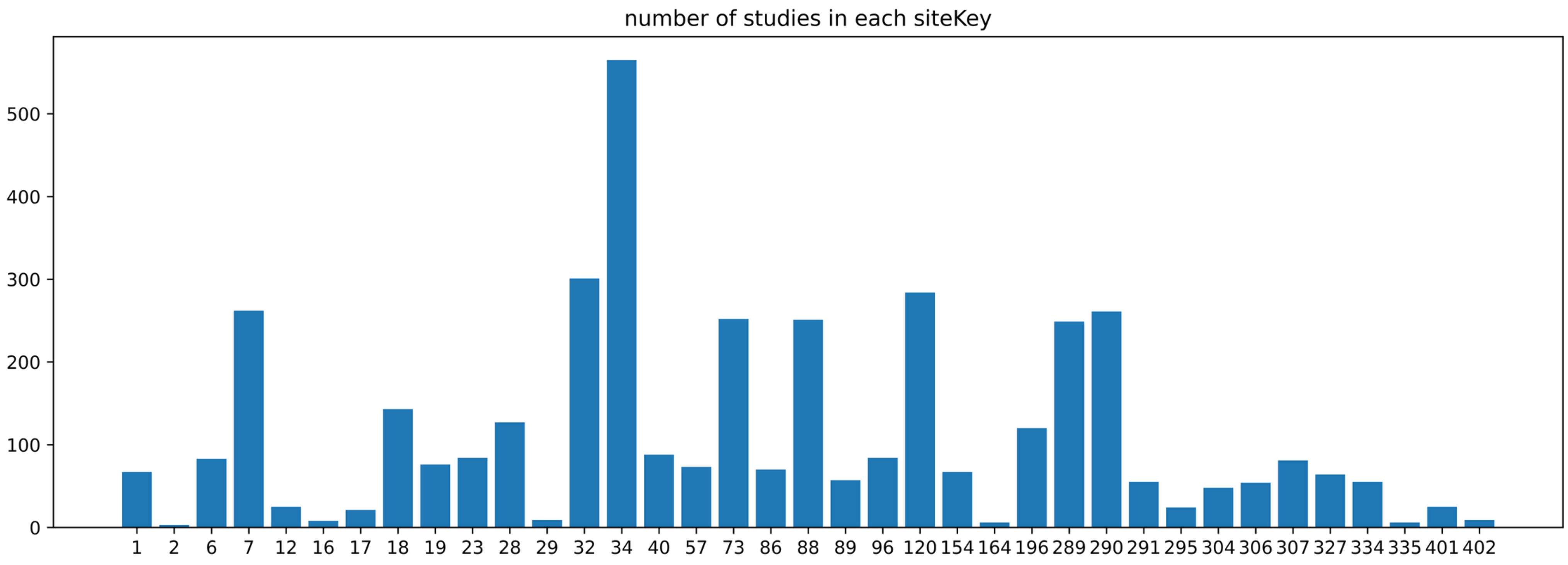


Tissue probability maps

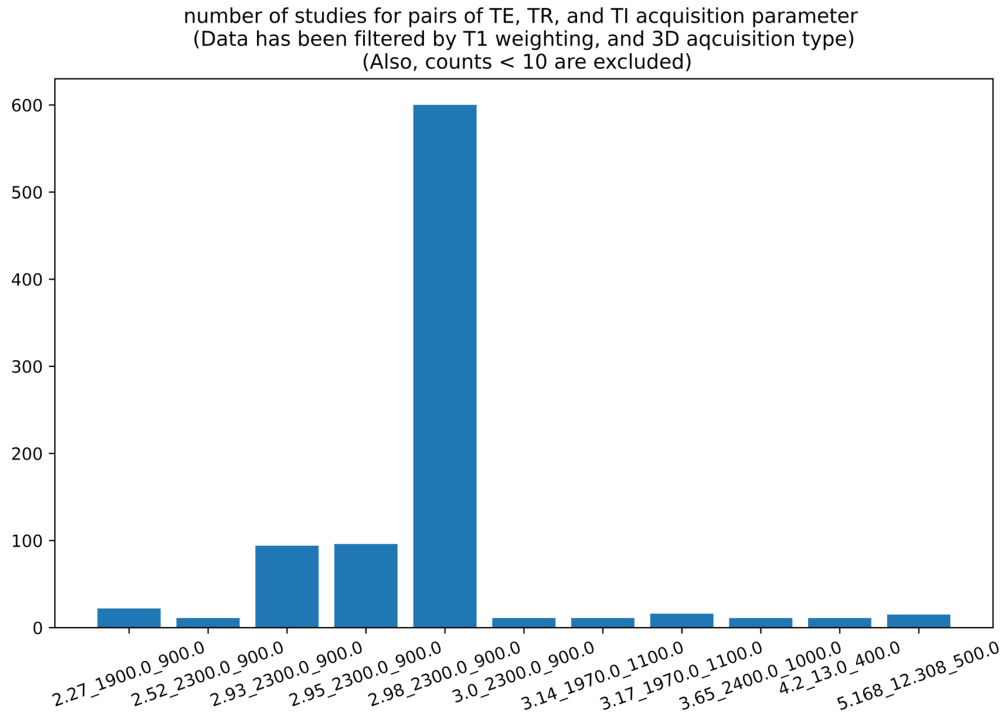
SECTION 3

EXPERIMENTS & RESULTS

SITEKEY IS NOT SITE



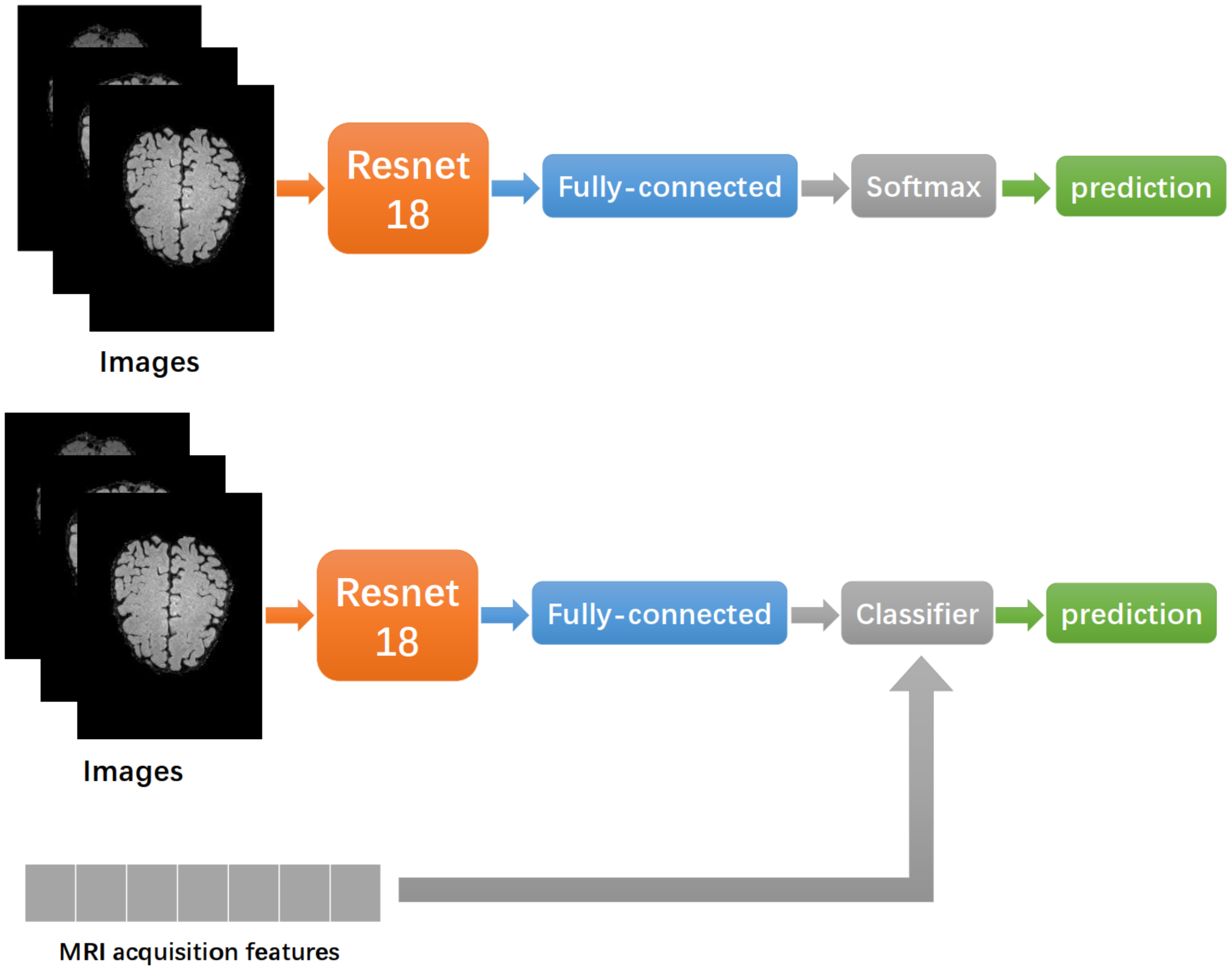
DIFFERENT MRI ACQUISITION PARAMETER



	Mfg Model	counts
0	Biograph_mMR	26
1	Prisma_fit	17
2	TrioTim	491
3	Verio	66

Experiment	dataset	Result (RF)	Result (DL)
Most frequent TE, TR, TI classification	unbalanced	random!!	random!!!
Most frequent TE, TR, TI classification	balanced	random!!	random!!
T2 vs T1 modality	unbalanced	-	0.94
T2 vs T1 modality	balanced	-	0.96

CLASSIFICATION MODEL

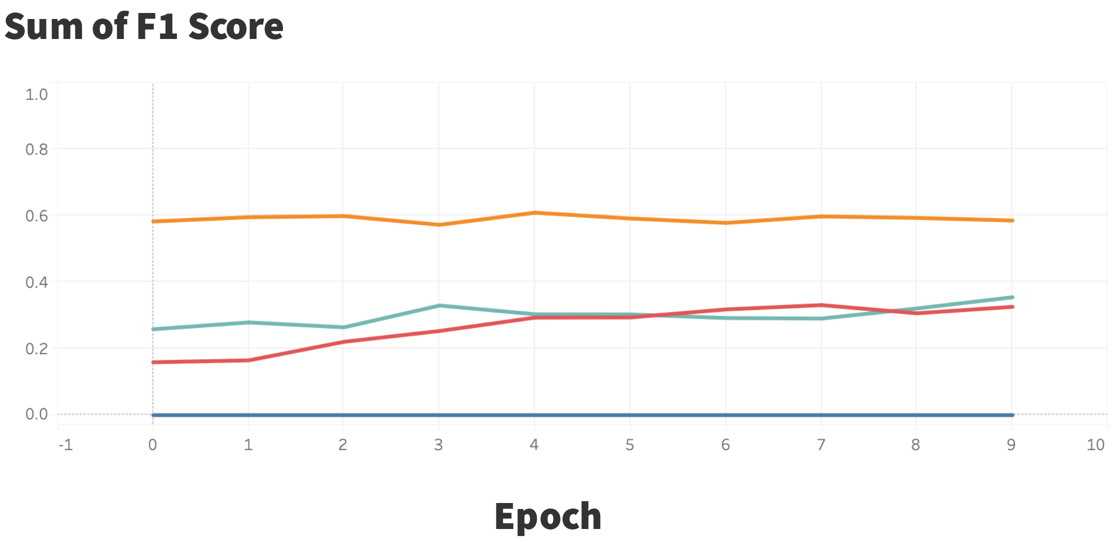


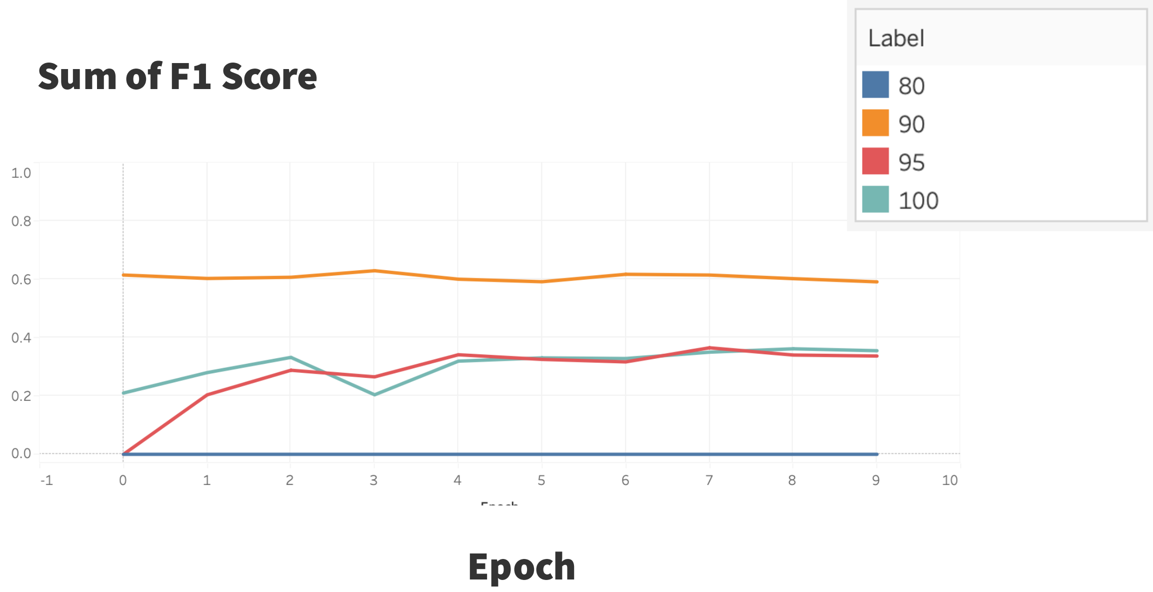
EXPERIMENT RESULT

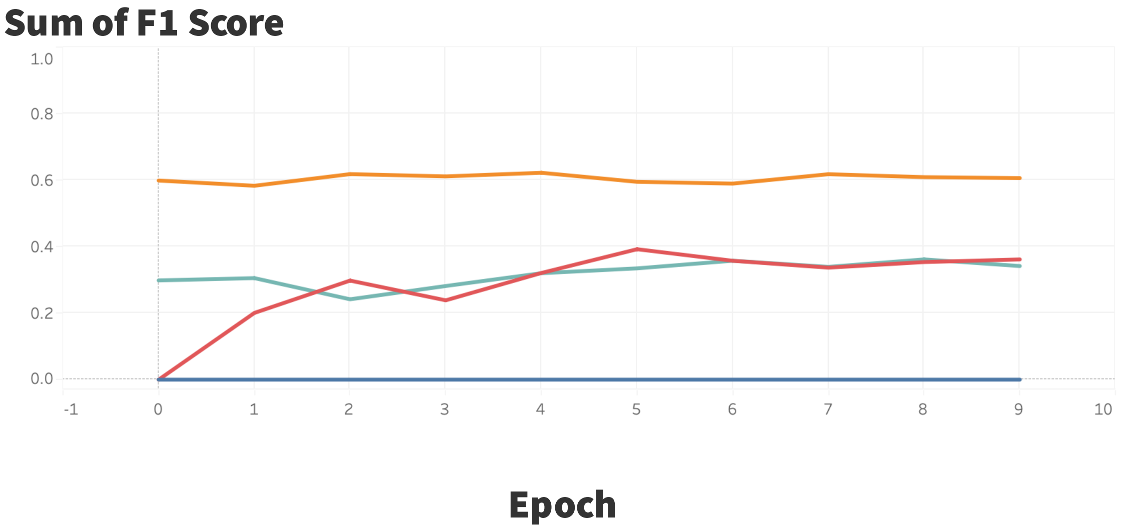
F1 scores for four most frequent schwab severity score

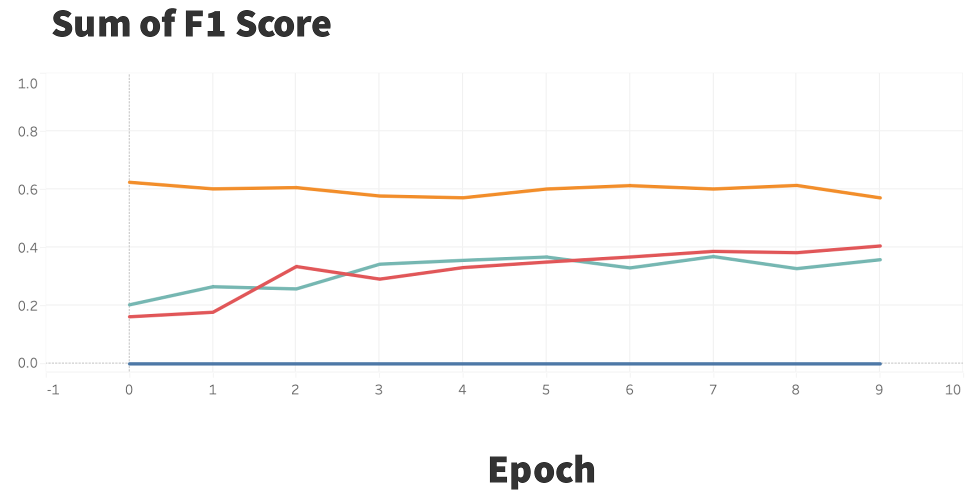
Version	Model	Features	80	90	95	100
v3	ResNet18, training all weights,	Preprocessed images	0	0.61	0.36	0.34
v4	Unfreeze two last Conv layer of ResNet18	Preprocessed images	0	0.61	0.34	0.34
v5	Unfreeze one last Conv layer of ResNet18	Preprocessed images	0	0.58	0.32	0.35
v6	Freeze all layers of ResNet18	Preprocessed images	0	0.60	0.36	0.34
v1_2	Freeze all layers of ResNet18	+ All MRI acquisition parameter	0	0.60	0.39	0.35
v3_2	Freeze all layers of ResNet18	+ Pulse Sequence	0	0.59	0.33	0.33
v4_2	Freeze all layers of ResNet18	+ TE	0	0.62	0.35	0.33
v5_2	Freeze all layers of ResNet18	+ TR	0	0.60	0.38	0.38
v6_2	Freeze all layers of ResNet18	+ TI	0	0.60	0.36	0.36
v7_2	Freeze all layers of ResNet18	+ Manufacturer	0	0.57	0.40	0.35
v8_2	Freeze all layers of ResNet18	+ Mfg Model	0	0.61	0.38	0.35
v9_2	Freeze all layers of ResNet18	+ TE, TR, TI	0	0.59	0.35	0.33

F1 SCORE OVER DIFFERENT EPOCHS









SECTION 4

DISCUSSION

FUTURE WORK

- Include other data included in PPMI dataset, like medical history for PD Severity classification, or use MDS-UPDRS score to improve the PD classification and then investigate if the MRI acquisition parameter are introducing any bias leads to acquisition shift in the dataset
- Instead of PPMI dataset, use another dataset that site information has been disclosed and our model is able to differentiate site of MRI acquisition and then investigate if MRI acquisition parameter introducing any bias
- Consult with MRI experts, MRI physicists or radiologist on importance and differences of MRI parameters

LIMITATION AND CONCLUSION

Limitations

- Use different dataset including the site key information
- Use MDS-UPDRS score for severity of PD classification and include other medical history instead of only focusing on MR images
- Explore images and parameters more by clustering control MR images using the features based on auto-encoder (fail to do so due to lack of time and GPU ram for now)
- Did not consider the longitudinal images in our study cohort

Concolusion

- It is necessary to draw the causal diagram and be aware of different biases, such as data mismatch or acquisition shift in medical imaging studies
- ML and DL model can focus and detect other difference in the images besides medical conditions and that is important to investigate more and find out what are the possibilities

THANKS FOR YOUR LISTENING!