The impact of MRI image quality on statistical and predictive analysis of Voxel-Based Morphology

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Introduction

- **T1w image quality significantly impacts derivative measures of brain morphology:**
  - Within scanner motion reduce gray matter volume & cortical thickness estimates
- **Accurate image quality assessment is critical for clinical diagnoses & research:**
  - No generally applicable quality standards or thresholds available
- **Several tools provide image quality measures (IQM): i.e. MRIQC, CAT12, Freesurfer**
  - Expert ratings show good to moderate but variable alignment with different IQMs

➢ ***Impact of quality on classical statistics or machine learning analysis is unclear***

Commonly, images with severe artifacts are excluded from analyses

➢ **Aim 1: Demonstrate the impact of image quality on univariate analysis**

➢ **Aim 2: Demonstrate the impact of quality on prediction models**

➢ **Data: AOMIC 1k P1/2, eNKI, CamCAN, SALD, 1000brains, GSP, DLBS**

➢ **Target: Effect of sex/gender on gray matter volume**

Methods

Image preprocessing

- **T1w segmentation with CAT12.8.1 (r2042)**
- **Modulated gray matter smoothed 4mm FWHM resampled at 8mm³**

❖ **3747 gray matter features**

- **Image Quality Rating (IQR) for raw T1w from CAT12**

Generation of sub-samples of low/high image quality

Quality sub-sampling

- **Massive age effects in VBM**

➢ **Balancing for age & sex**

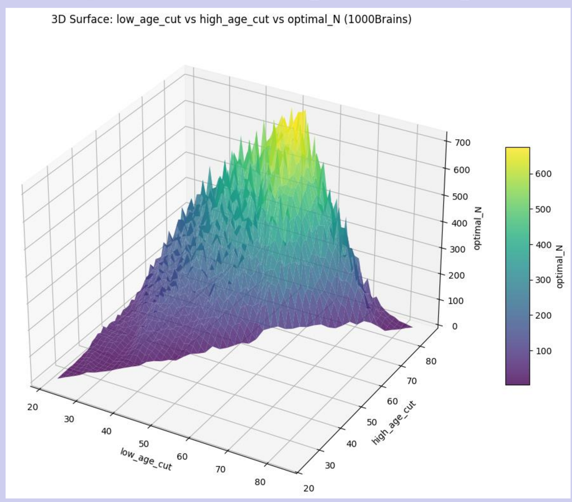
I. Divide into 3/10 age bins

II. Retain same N for each sex

III. Takes 60% lowest/highest IQR

❖ **low/high quality sub-samples**

Optimize age range

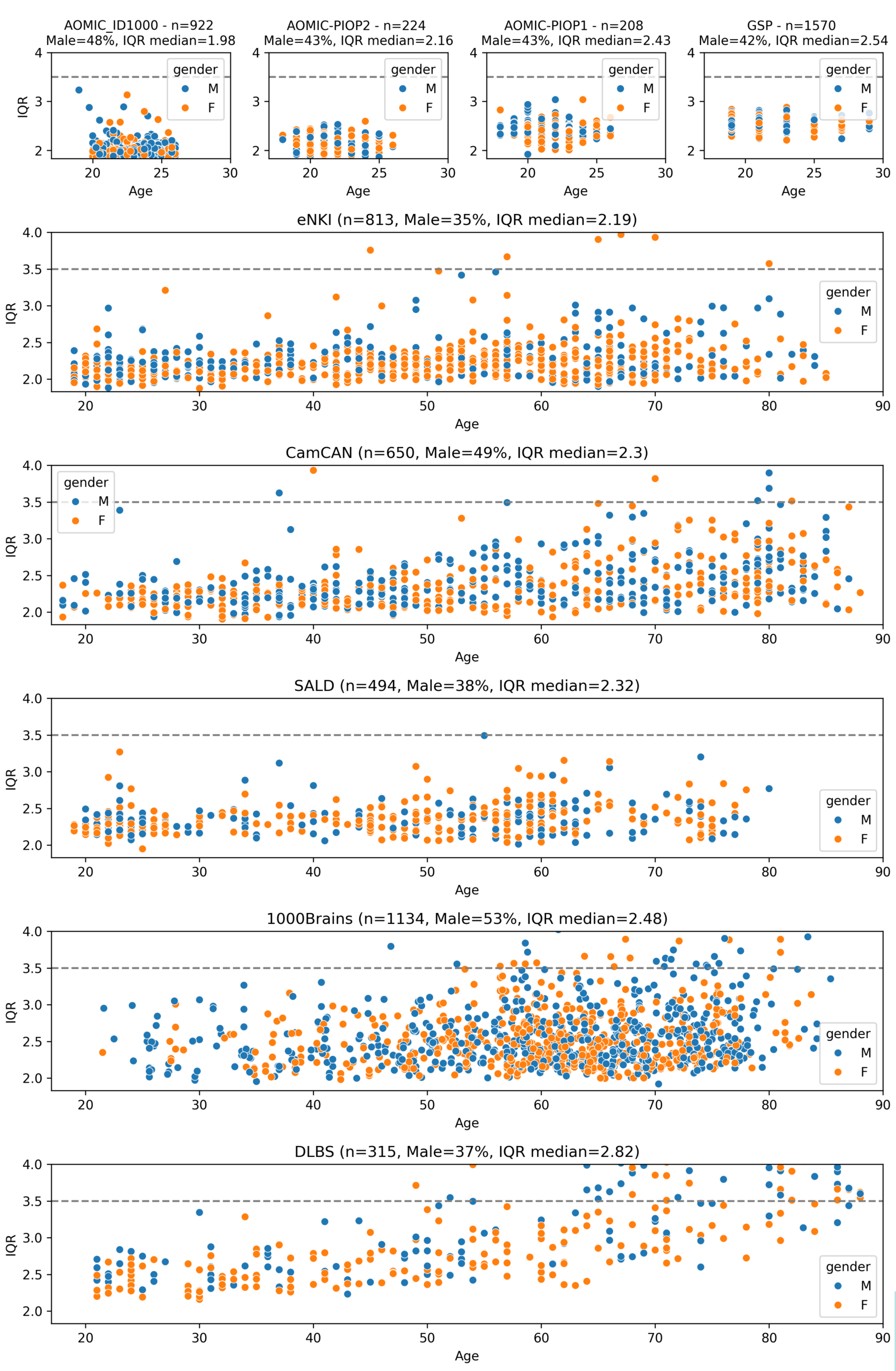


Sub-samples

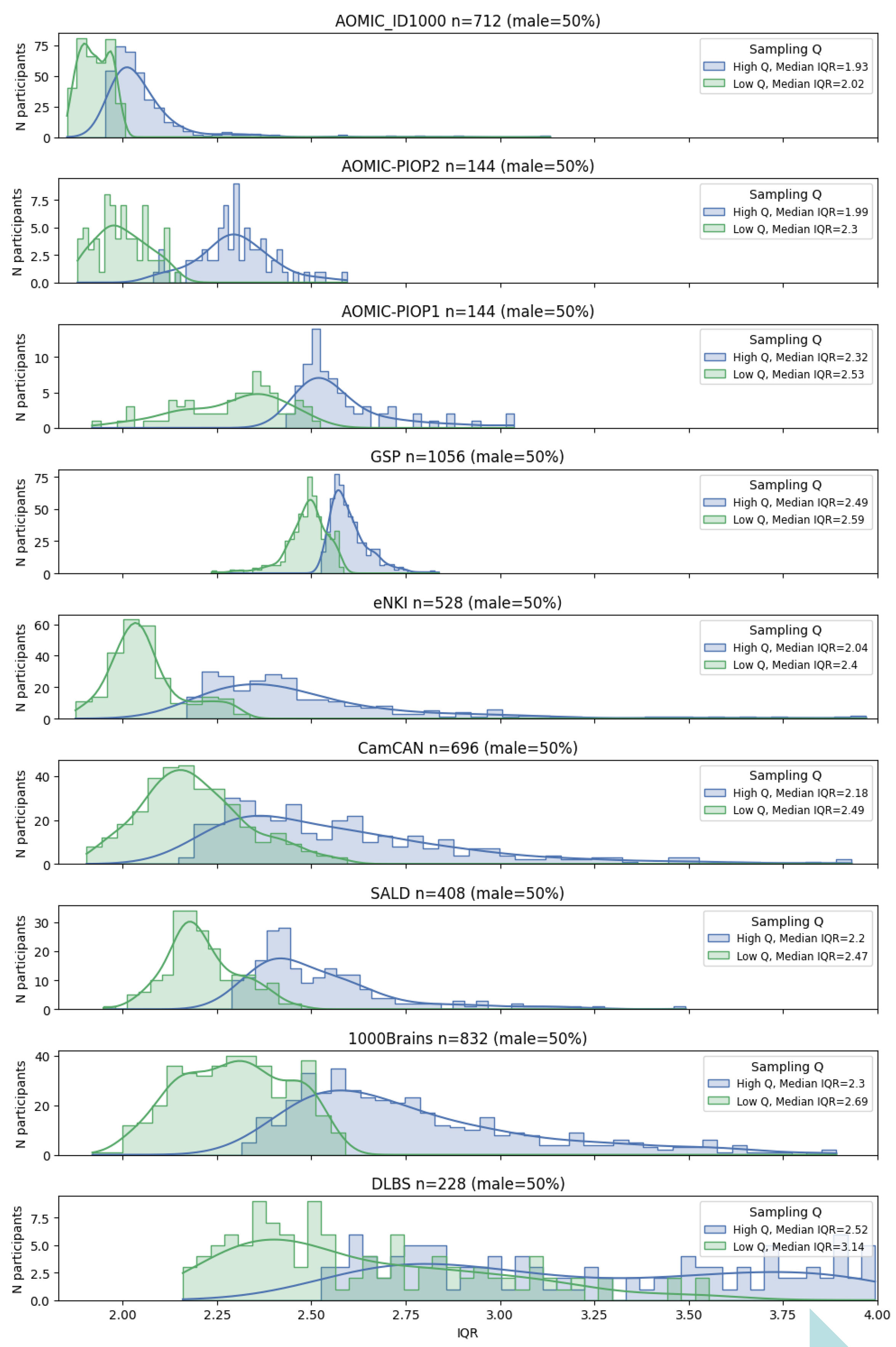
Site	Original N	N	N share (%)	IQR Diff
AOMIC_ID1000	922	356	82 (23%)	0.128
AOMIC-PIOP2	226	72	4(5%)	0.299
AOMIC-PIOP1	215	72	7(9%)	0.291
GSP	1570	528	79(14%)	0.149
eNKI	812	264	26(9%)	0.098
CamCAN	650	348	91(26%)	0.389
SALD	494	204	24(11%)	0.315
1000Brains	1126	416	111(26%)	.0.479
DLBS	283	114	9(7%)	0.595

Data

Full samples image quality, sex and age

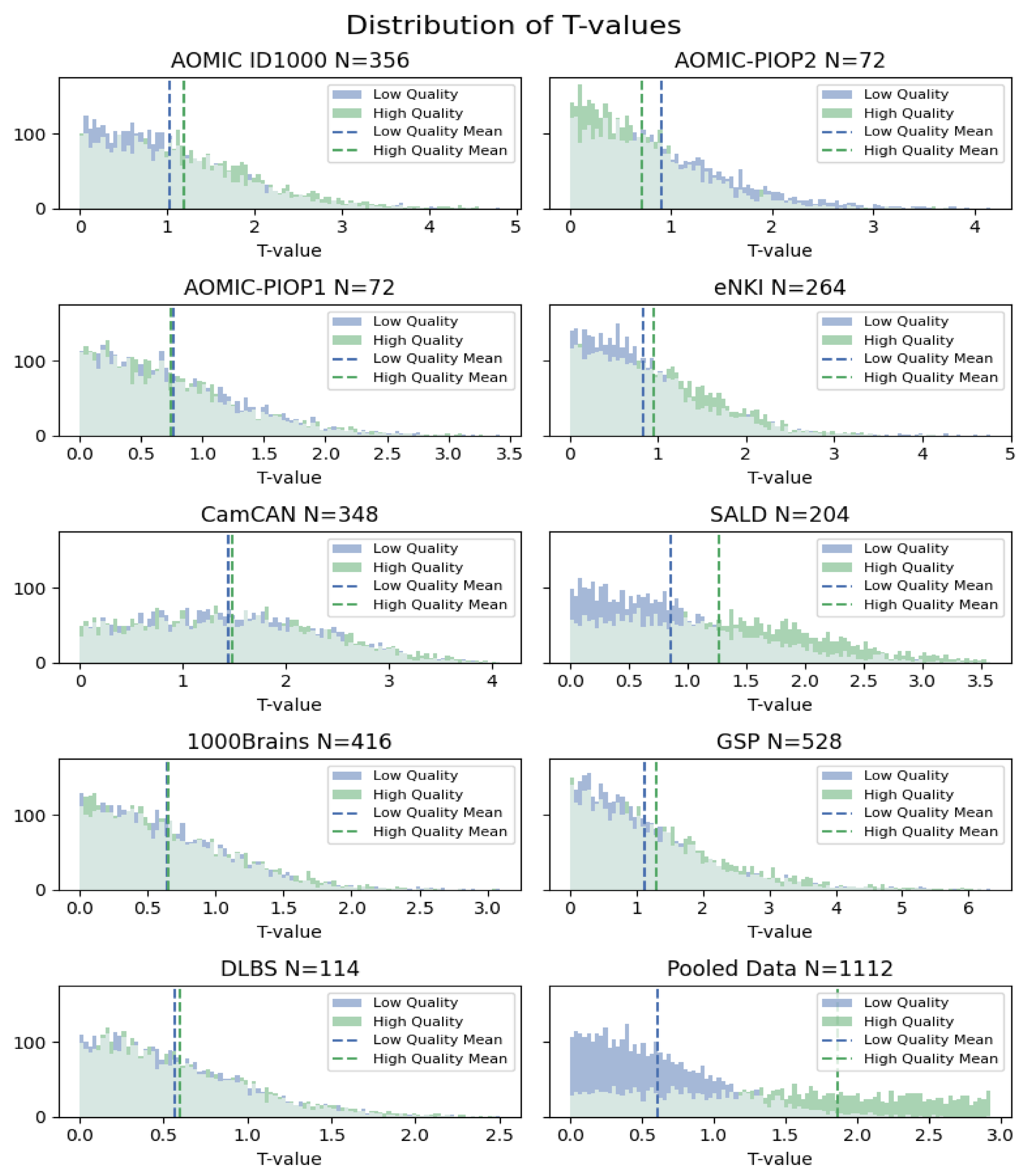


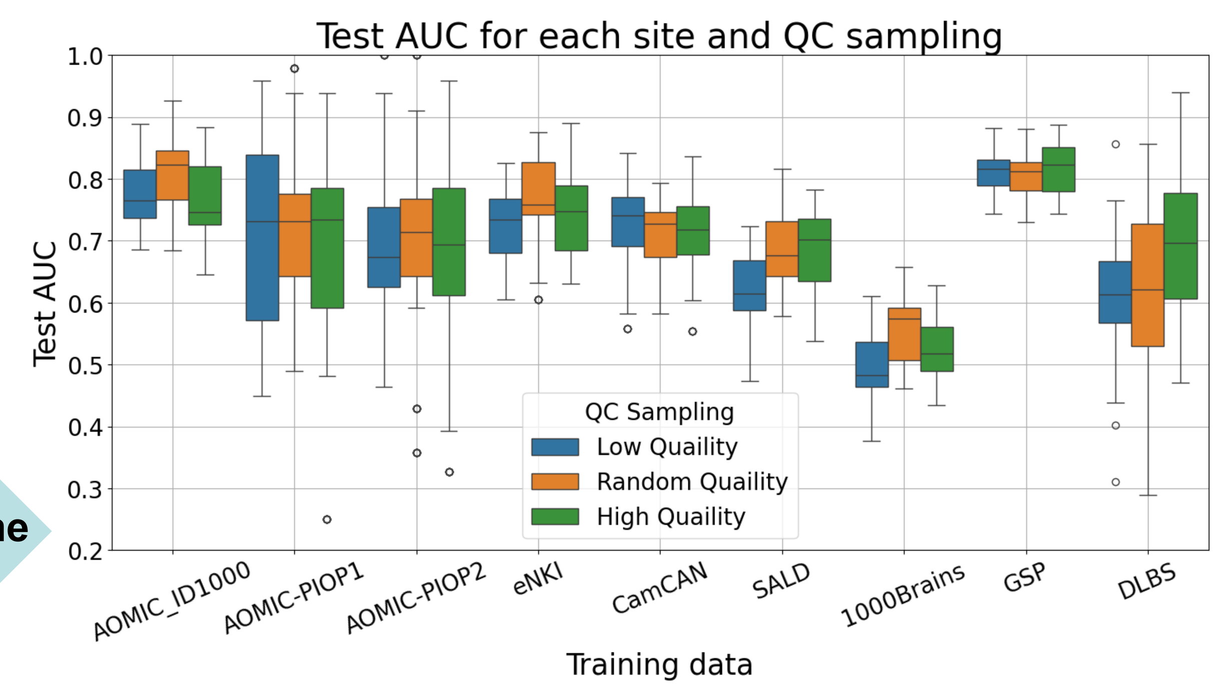
Sub-sample image quality



Sex/gender prediction via logistic regression
leakage-free confound regression of total intracranial volume
5 fold cross validation with 5 repetitions

Feature wise t-test after brain size regression





Discussion

- **In mass uni-variate analyses, poorer image quality results in lower sensitivity for sex differences.**
  - ➢ **Higher image quality with lower N might help detecting effects in classical group comparisons.**
- **Machine learning based sex classification is largely independent of image quality for acceptable scan quality.**
  - ➢ **Machine learning models in contrast to classical statistics seem quite robust to variable image quality.**

References

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