Image Quality Transfer in MRI with Deep Neural Networks

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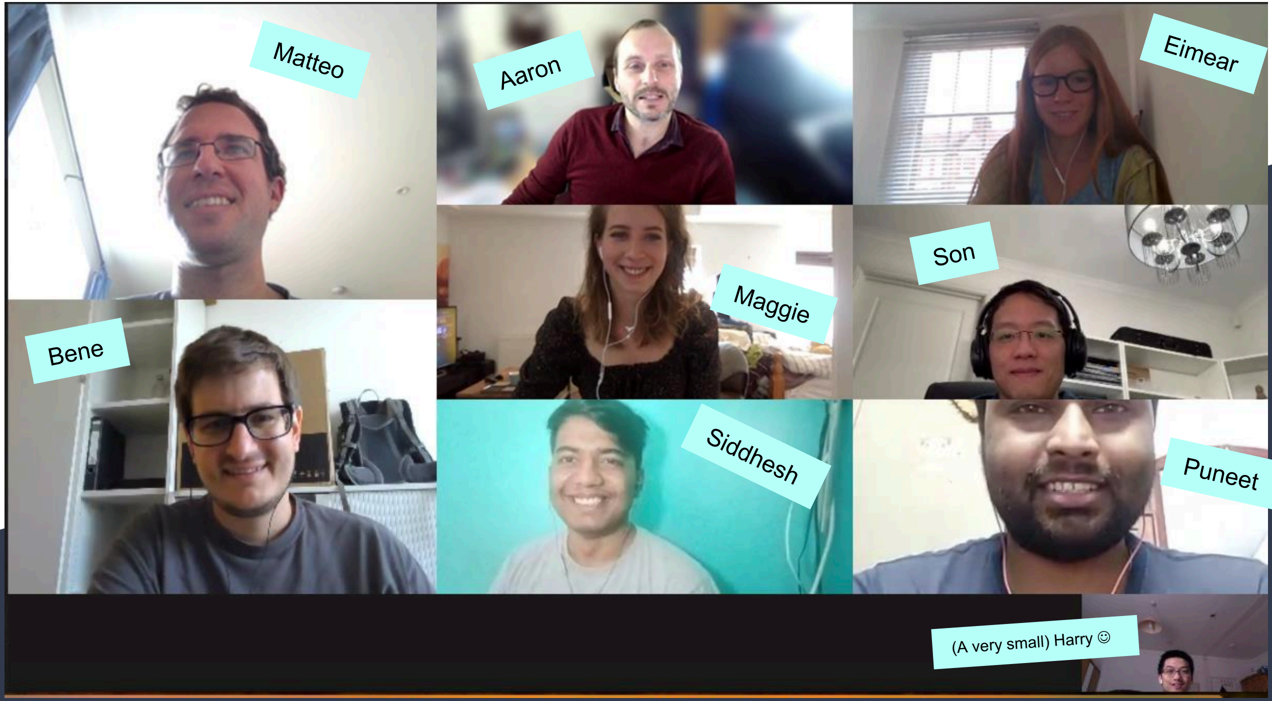

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Motivation

Diagnostic Utility of MRI

Clinical effectiveness as Field Strength

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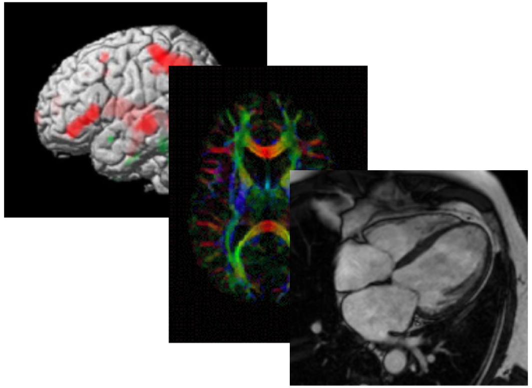
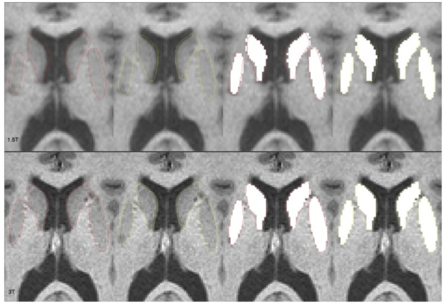
High SNR/CNR/Spatial Resolution

Improved Measures (segmentation, visual rating)

Better informed diagnostics, trajectory predictions & treatment plans

Lack of Access to >1 T MRI in LMIC populations where MRI could prove vital (e.g. Nigeria - epilepsy most common paediatric neurological disorder)





1.5T

3.0T

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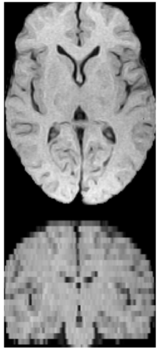
https://www.google.com/maps/d/u/1/viewer?hl=en&ll=15.011638546555254%2C-34.14334029214468&z=3&mid=1dXG84OZIAOxjsgh3x2tGzWL1bNU



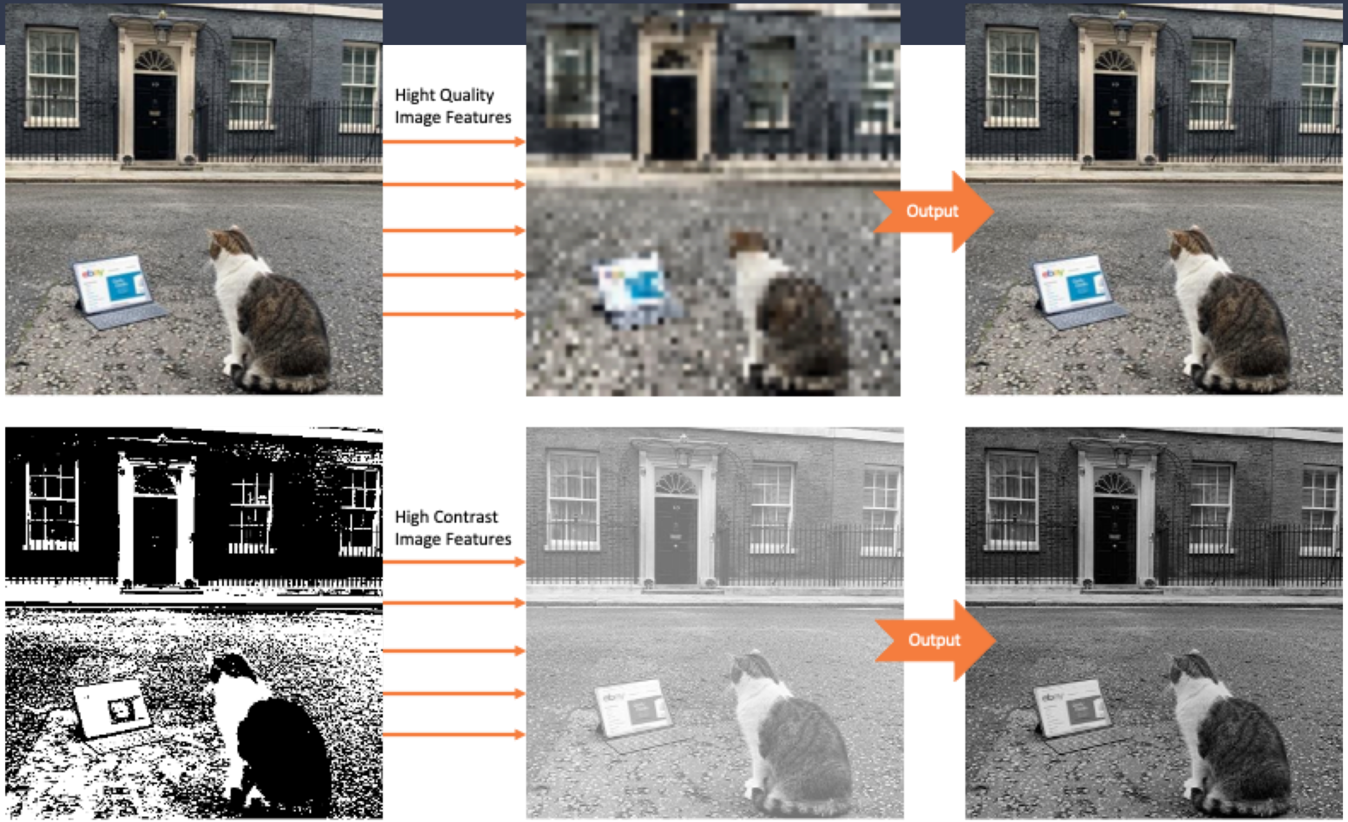
Is there a cost effective and practical solution to improving LF-MRI scan quality that could be used to effectively assist clinical decisions?

MF

IQT – the solution?

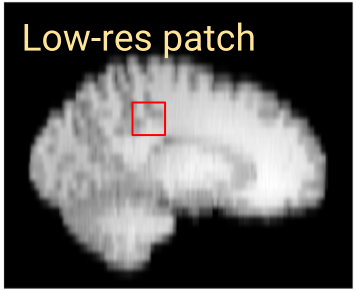
- **Image quality transfer (IQT)** is a class of techniques for mapping features from high quality images to low quality images

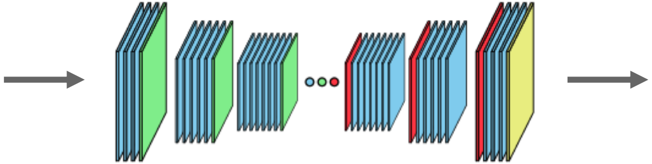
- It can also be used to **improve contrast** in low contrast images (e.g. T1W) by taking features from high contrast images (e.g. T2W)



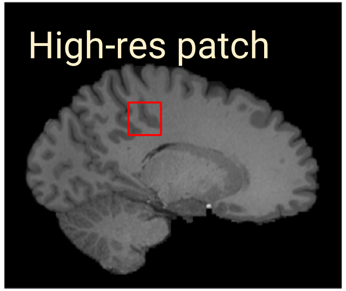
Approach

A. Pipeline

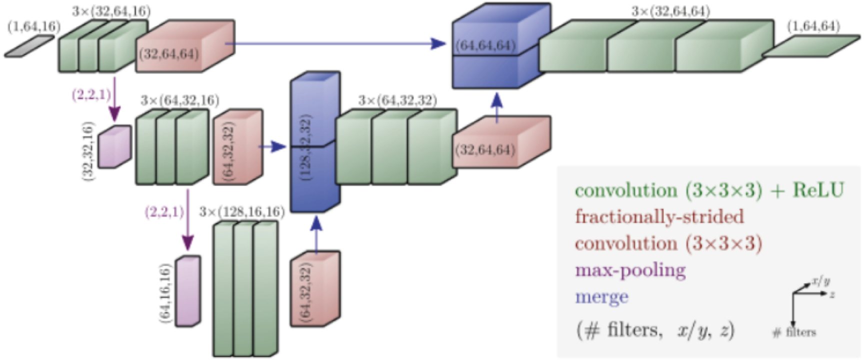




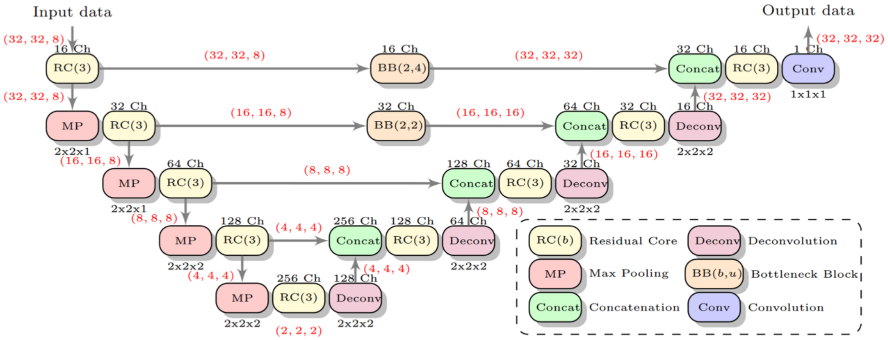
CNN



B. CNN backbone

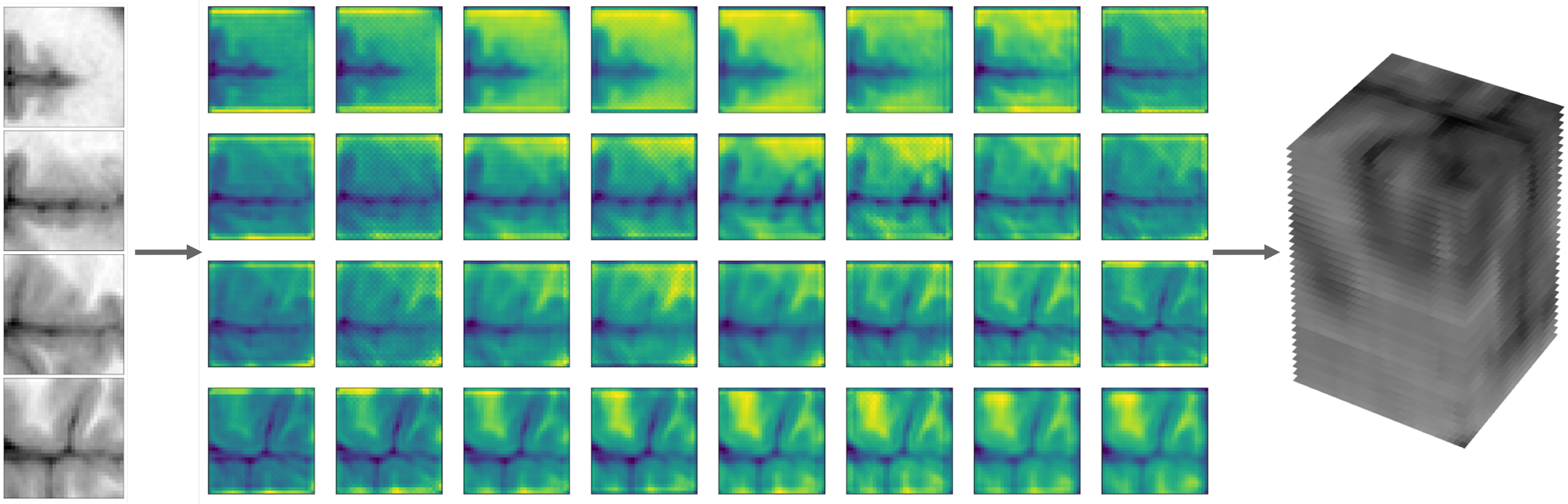


3D SRU net (Heinrich et al, 2017)



Anisotropic U-Net Architecture (Lin et al, 2019)

Network Pipeline



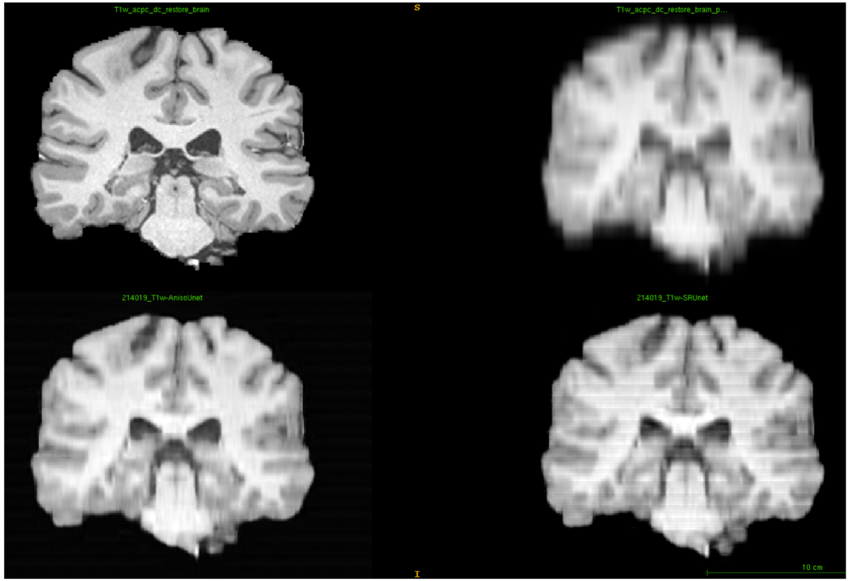
Input
32x32x4

Final Layer Activation Maps
32x32x32

Output
32x32x32

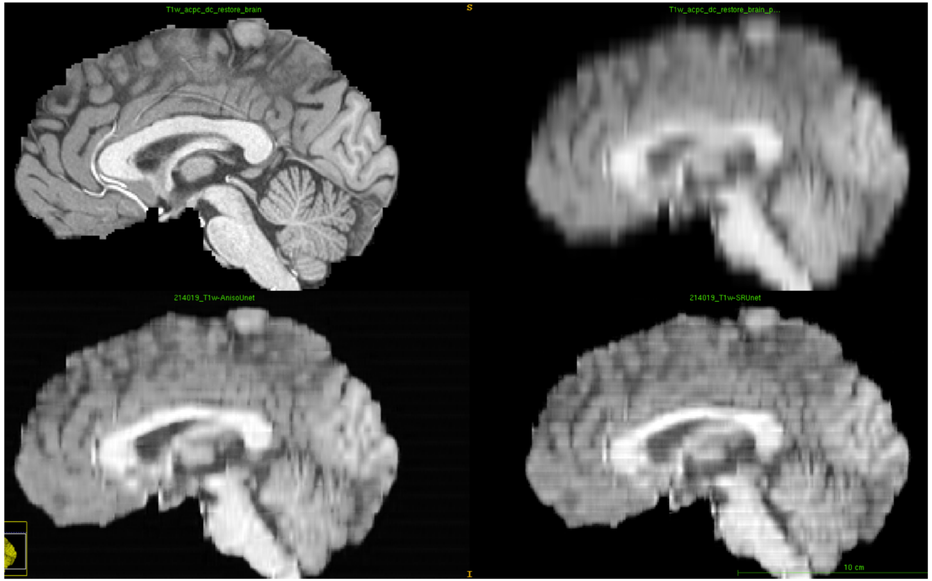
Project Results

Original 3T   Simulated LR MRI



After IQT w/ **AnisoUnet**   After IQT w/ **SRUnet**

Original 3T   Simulated LR MRI

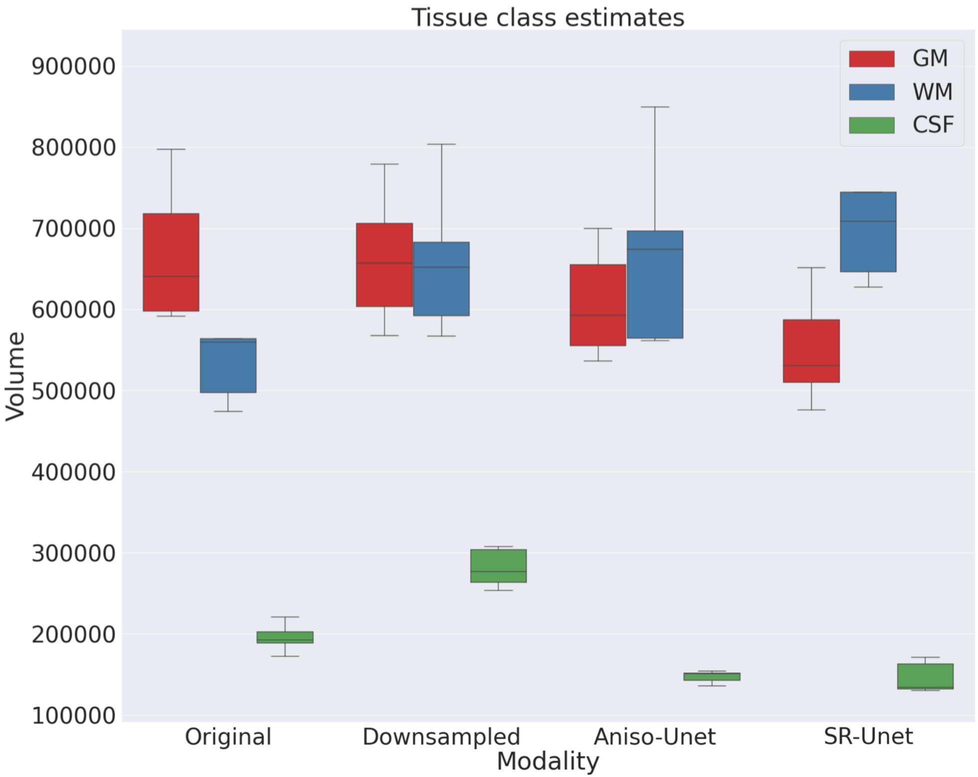


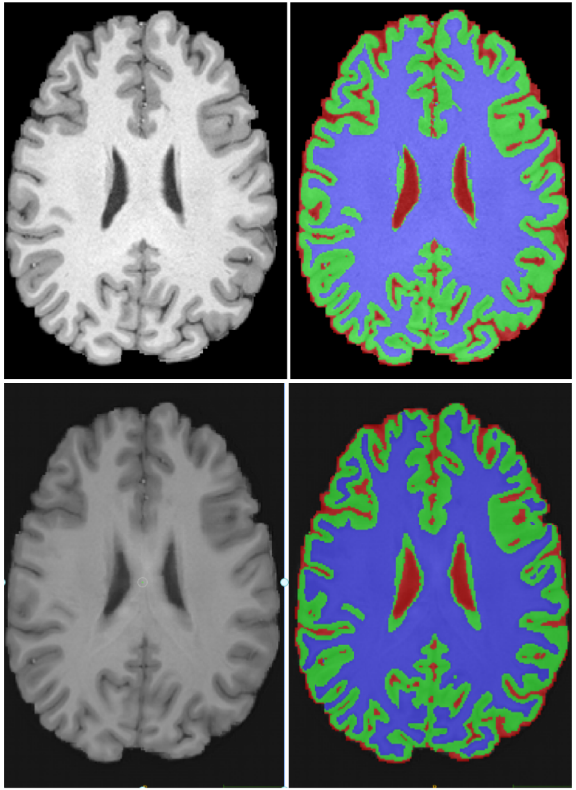
After IQT w/ **AnisoUnet**   After IQT w/ **SRUnet**

BW

Additional Analyses

Tissue Class Result: Test Dataset





Results: Test Dataset

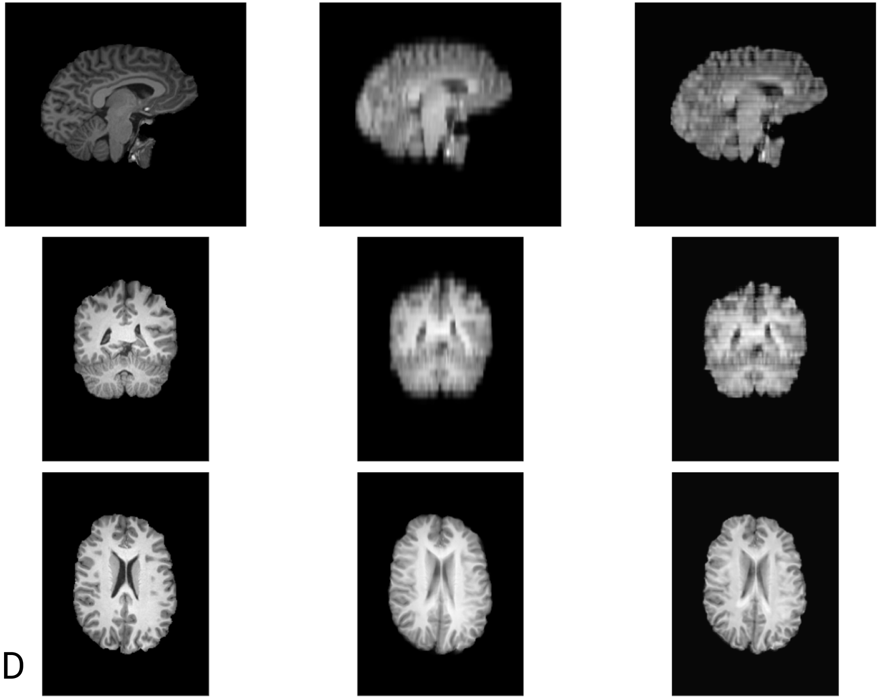
Metric (mean)	Original data	SR-Unet	Aniso-Unet
GM Volume (mm^3)	669167	551322	608002
WM Volume (mm^3)	559878	726987	669331
CSF Volume (mm^3)	195537	146273	147249
RMSE	---	74.24	70.92
SSIM	---	0.73	0.74
PSNR	---	30.43	30.83

PD*Additional Analyses*

Testing on external dataset: MDD (Major Depressive Disorder)

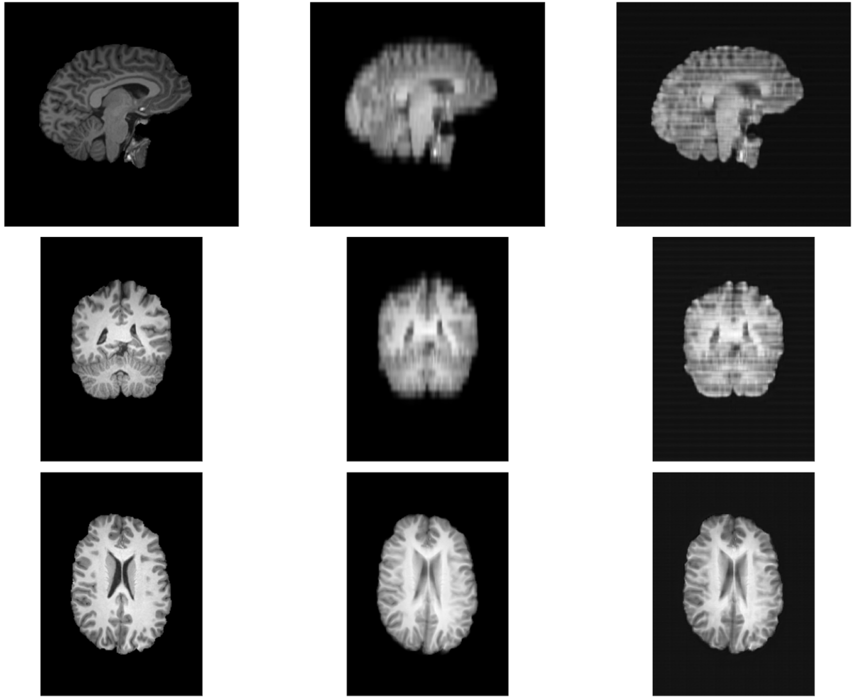
MDD Sub - SR-Unet(32,32,4)

HR 3T image | Simulated image | Reconstructed



MDD Sub - Aniso-Unet(32,32,4)

HR 3T image | Simulated image | Reconstructed



PD

Evaluation Metric's Result

Table: The performance of the model's on up-scaling factors 8. The mean and standard deviation of PSNR and the mean SSIM (MSSIM) are calculated over 5 evaluation subjects.

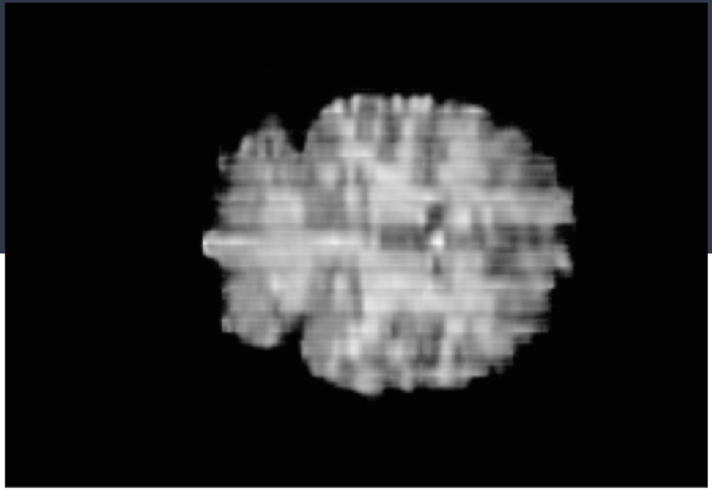
Method	PSNR(dB)	MSSIM
SR-Unet	27.845 ± 2.451	**0.635 ± 0.023**
Aniso-Unet	**28.162 ± 2.356**	0.625 ± 0.018

Table shows the mixed performance between the two model, ANISO-Unet achieved the best performance in terms of the average PSNR whereas SR-Unet showed best performer in MSSIM.

Note: Statistical test can not done due to small sample size (N=5).

The higher the PSNR and MSSIM, the better the quality of the compressed or reconstructed image.

Issues of the patch-based approach



Due to the higher dimensional dataset, the patch might be a better option than the entire image analysis.
However, there might be some trade-off:

- A small step size(strides) is computationally intensive.
- Small patch size along-with overlapping(depends on step size) might give redundant information.
- A non-overlapping patch might result in loss of contextual information for a continuous region.
- Small patch size might also result in loss of contextual information.
- A larger patch size might introduce an error in localization.
- Misalignment issues can often occur using the patch based method when simulated quality images are not created from the original scans (Blumberg et al. 2019)
- Tiling artefact as a result of the patches not stitching correctly. (especially in the Aniso-Unet run)
- During inference, increasing the patch size increases the RMSE, SSIM.

AL

Safety of IQT in Clinical Settings

- Consider where IQT is applied to imaging in a clinical setting (e.g. embedded post-processing)
- False negatives - obscures malignant findings and reduces likelihood of detection
- False positives - benign features appear malignant which leads to unnecessary follow-up
- Types of errors in IQT
  - Parameter uncertainty - results from finite training set
  - Intrinsic uncertainty - results from the 1:many nature of upscaling
  - Model bias - limitations of model to represent the problem (assumed small in DNN)
- Enhanced images co-presented with warning maps flagging uncertain features
- Deployed IQT may also be classed as a medical device requiring clinical validation & regulatory hurdles


ANY QUESTIONS???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