An Enhanced Architecture for Accelerating Magnetic Resonance Imaging Based on Res-U-Net



Vincenzo Colella

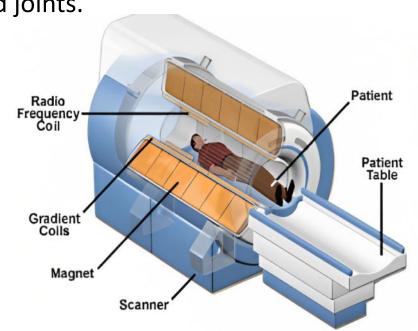
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Background

 Magnetic Resonance Imaging is a safe and reliable technique of medical imaging.

 MRI is used to diagnose a wide range of medical conditions as injuries, tumors and diseases affecting various parts of the body, including the brain, spine, and joints.



Problem Statement

- MRI scans typically last 30-90 minutes under normal conditions.
- Staying still for the entire duration of an MRI procedure can be challenging for many individuals.
 - Claustrophobic individuals
 - Urgent MRIs (traumatic brain injuries, spinal cord injuries...)
 - Children and babies may require general anaesthesia to stay still
 - Elderly individuals may experience difficulties staying still during an MRI due to age-related conditions.

Problem Statement

- Sometimes image quality is compromised in favor of tolerable scan times.
- Advancements in MRI technology have made it possible to obtain images faster while keeping image quality.
- The use of AI technology in MRI scans has the potential to revolutionize medical imaging and improve patient outcomes.

→ Our objective is to improve the accessibility and effectiveness of MRIs by enhancing the speed of MR scans by up to 8 times.

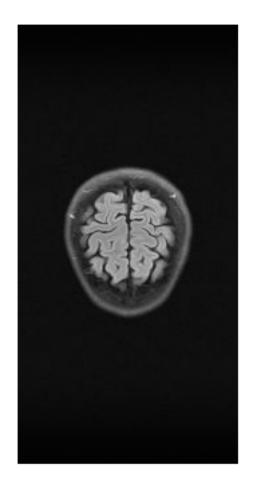
State of the Art

- FastMRI is a collaborative research project to investigate the use of AI to make MRI scans faster, designed by Facebook AI Research and NYU, which provided the dataset.
- In 2020, there have been 19 submissions from around the world and AIRS Medical, a South Korean private company, won the challenge with an average SSIM (Structural Similarity Index) of 0.96.
- The FastMRI challenge 2020 involved two categories: the single-coil knee MRI and multi-coil brain MRI, and two accelerating factors: 4x, and 8x.

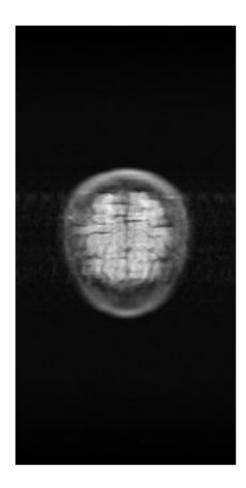
Our Approach

- Our approach uses a neural network, the Res-U-Net, designed and implemented in combination with two preprocessing algorithms,
 GRAPPA and ESPIRIT, to process brain MRI scans obtained with a multicoil approach.
- Our work focuses on the 4x and 8x acceleration factors in scans.
 - To simulate the 4x acceleration, I kept only **75%** of the available image data, meaning around **25%** of k-space data.
 - For the 8x acceleration, I kept only 60% of the image data, equal to
 12.5% of k-space data.

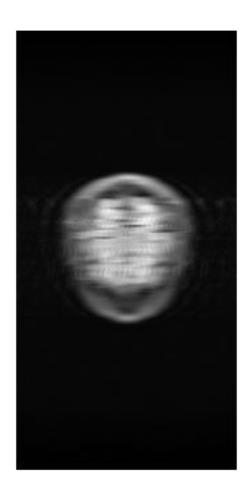
Undersampling Data





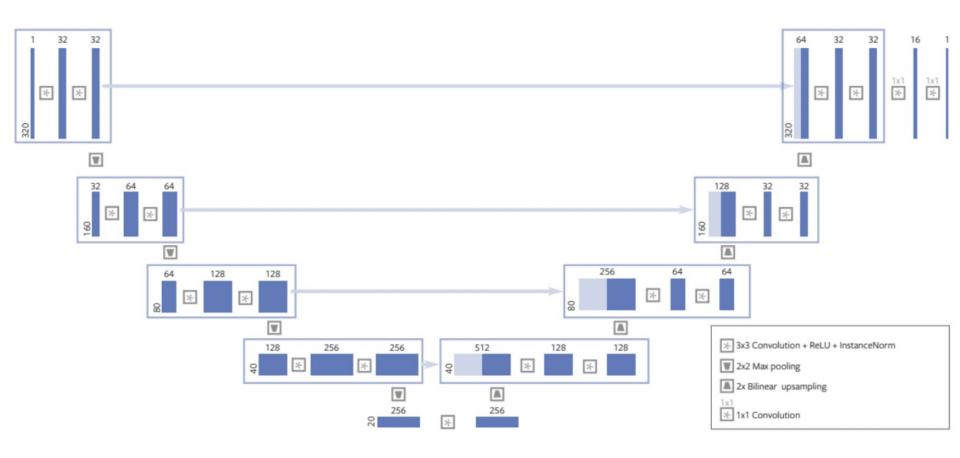


4x Masked Image



8x Masked Image

Res-U-Net



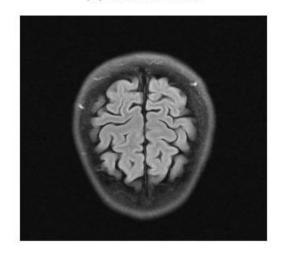
Dilated Convolutions

Residual Blocks

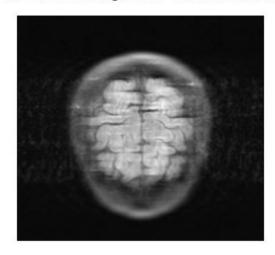
Generalized Autocalibrating Partially Parallel Acquisitions

 GRAPPA is a type of parallel imaging technique that exploits the spatial information redundancy in the data to reconstruct the image from undersampled k-space data, using a linear combination of adjacent k-space data points.

(a) Ground Truth



(b) Masked Image with 4x Acceleration



(c) Reconstructed Image after GRAPPA

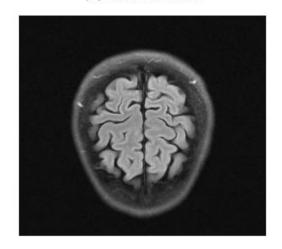


SSIM: 0.74 SSIM: 0.77

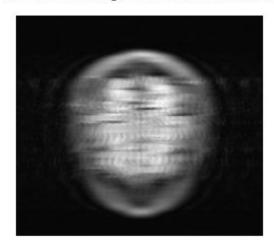
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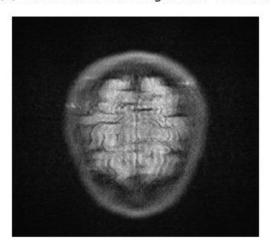
(a) Ground Truth



(b) Masked Image with 8x Acceleration



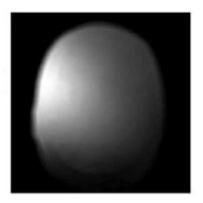
(c) Reconstructed Image after GRAPPA

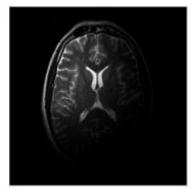


SSIM: 0.60 SSIM: 0.68

An Eigenvalue Approach to Autocalibrating Parallel MRI

- ESPIRIT simultaneously estimates the coil sensitivity maps and the missing k-space data using an eigenvalue decomposition method.
- This is done by rewriting the image as an eigenvector, with the coil sensitivities encoded by the eigenvectors with largest eigenvalues and the masked data encoded by the eigenvectors with smallest eigenvalues.





Training

- I trained the Res-U-Net using two different instances of the dataset.
- The preprocessing of the data started with the fully sampled image being masked to simulate undersampled data (4x or 8x).
- After that I applied GRAPPA, ESPIRiT and then fed the data to the Res-U-Net.
- I trained the network for 50 epochs using SSIM as loss function.



Discussion

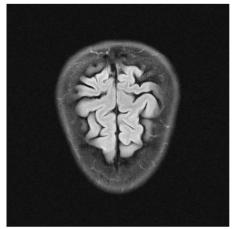
Summary of SSIM results for each team in the FastMRI 2020

Team	4x Track	8x Track	Average
AIRS Medical	0.964	0.952	0.958
ATB	0.960	0.944	0.952
Neurospin	0.959	0.942	0.9505
\mathbf{Ours}	0.9284	0.8984	0.9134

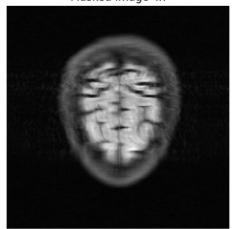
- The architecture had an average SSIM of **0.9284** for the 4x track and **0.8984** for the 8x track when tested on the validation split.
- Our model achieved results comparable to those of the top 3 teams in the competition.

Discussion

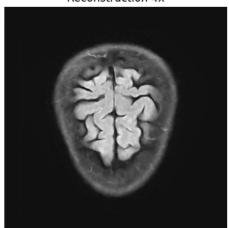
Ground Truth



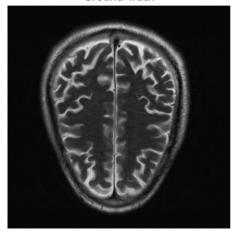
Masked Image 4x



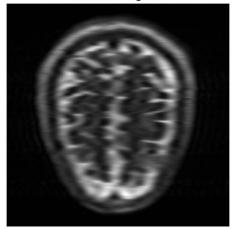
Reconstruction 4x



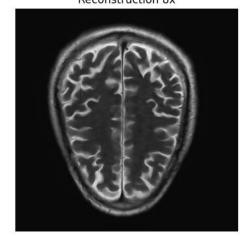
Ground Truth



Masked Image 8x

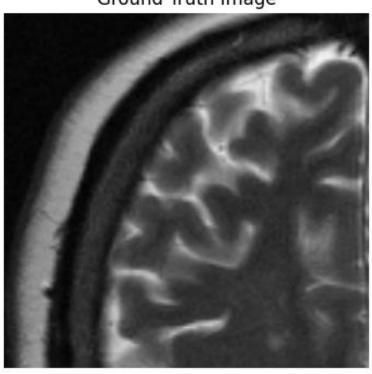


Reconstruction 8x

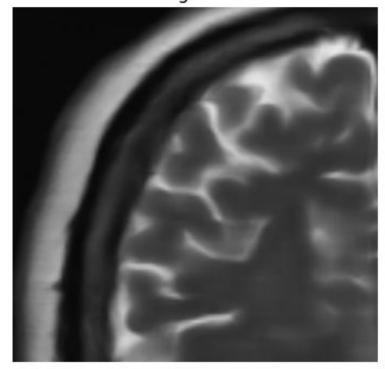


Discussion - 4x

Ground Truth Image

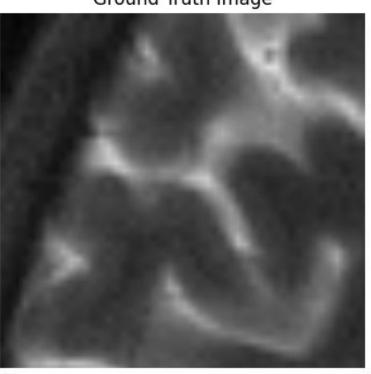


Reconstructed Image with SSIM = 0.9284

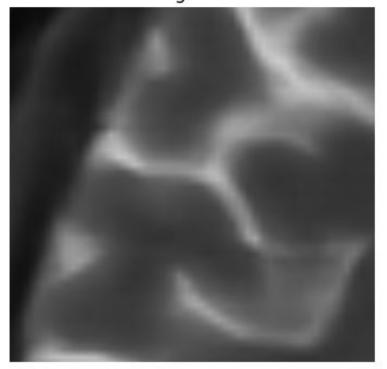


Discussion - 4x

Ground Truth Image

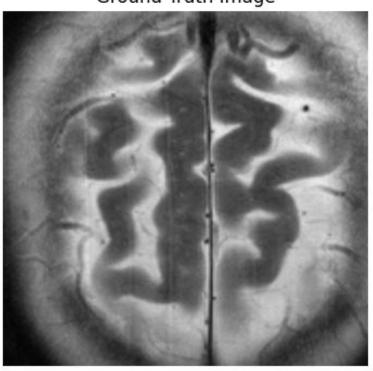


Reconstructed Image with SSIM = 0.9284

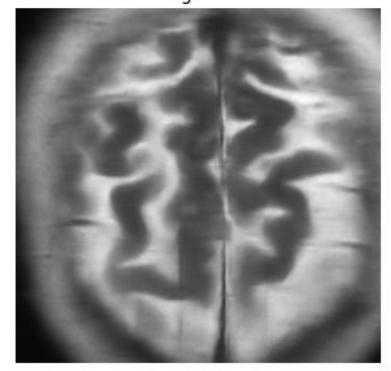


Discussion - 8x

Ground Truth Image



Reconstructed Image with SSIM = 0.8984

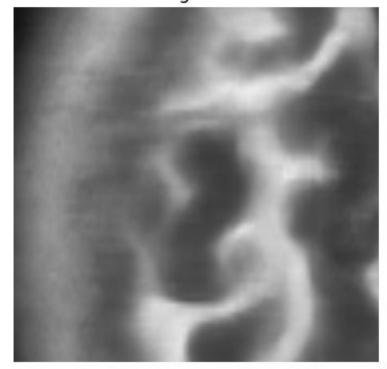


Discussion - 8x

Ground Truth Image



Reconstructed Image with SSIM = 0.8984



Conclusion

- The project achieved impressive performance in the 4x track, despite a few instances of "hallucinations".
- The outcomes of the 8x track require further enhancement.
- Radiologists state that the images from the 4x accelerated scans are comparable to fully sampled images, while the 8x accelerated images are still not deemed suitable for use in a medical environment.
- → The proposed architecture has resulted in successful acceleration of MRI scans while maintaining high-quality images, although further improvements can still be made to achieve the best possible outcome.

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