Computational Imaging Lab

Report of Computional Imaging Project

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1 Introduction

In the past few decades, Magnetic Resonance Imaging (MRI) technology has achieved significant advancements, evolving from basic imaging methods to the capability of providing high-resolution, multi-parametric imaging. Despite these advancements, a primary challenge of MRI remains its slow imaging speed, which limits its feasibility in certain clinical and research applications. To accelerate the MRI imaging process, researchers have developed various image reconstruction methods based on advanced mathematical models and deep learning techniques.

Recently, deep learning methods have attracted considerable attention for their outstanding performance in image processing domains. Compared to traditional model-driven approaches, deep learning-based methods can directly learn complex image features and structures from a vast amount of data, offering new possibilities for MRI image reconstruction.

In particular, Model-Driven Deep Learning (MoDL) approaches combine the rigor of traditional mathematical models with the flexibility of deep learning models[1], providing an effective new avenue for accelerated MRI. It utilizes Convolutional Neural Networks (CNN) as a regularization prior, integrated with a traditional image reconstruction framework, proposing a systematic deep architecture for solving inverse problems. This method demonstrates a smaller network parameter requirement and faster training speed. Besides, we discuss the Variational Network (VarNet) approach[2], which directly incorporates deep learning models into the variational model, achieving more precise image reconstruction through end-to-end training. What’s more, we also investigate the self-supervised learning approach (SSDU)[3], which employs a physics-guided network training strategy, allowing deep learning models to learn effectively even in the absence of a large amount of labeled data.

By applying and comparing these three methods on the same fastMRI dataset, we aim to assess their effectiveness and potential in accelerating MRI image reconstruction. This study not only provides insights into the deep understanding of deep learning methods' application in MRI image reconstruction but also holds significant implications for the future development of more efficient and accurate imaging technologies.

2 Methods

2.1 Dataset and Preprocessing

We utilized a public fastMRI dataset containing axial T2 brain scans and conducted a series of preprocessing steps to simulate accelerated MRI acquisition and prepared the data for deep learning-based reconstruction.

Normalization: K-space data from each image was normalized by its maximum absolute value to ensure uniformity across the dataset.

Ground Truth(GT): Utilizing SigPy, the ground truth images were reconstructed from k-space using the inverse Fast Fourier Transform (iFFT) followed by the root sum of squares (RSS) method. And the images were resized to 384x384 pixels for standardization.

Coil Sensitivity Maps (CSM): Coil sensitivity maps were computed for each slice using sigpy's EspiritCalib function to simulate multi-coil MRI acquisition scenarios.

Undersampling Masks: Cartesian masks with an acceleration factor of 2x, 4x and 6x were created and applied to the k-space data to mimic accelerated MRI acquisition.

Data Splitting and Storage: The dataset was divided into training and testing sets, with all preprocessing steps applied independently to each. The processed data, including CSM, undersampling masks, and ground truth images, were stored in an HDF5 file for efficient model training and evaluation.

2.2 Image Reconstruction Methods

We evaluated three deep learning-based MRI image reconstruction methods: MoDL, VarNet, and SSDU approaches. Each method was implemented using the PyTorch framework and trained and tested on HPC equipped with NVIDIA GPUs.

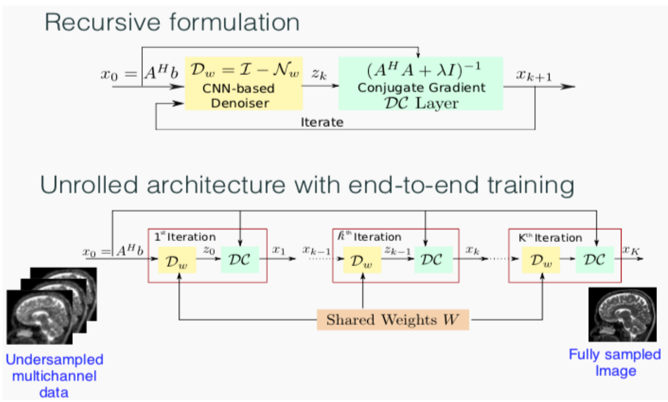

Figure 1: MoDL architecture[1]

Figure 1 shows the architecture of MoDL, it takes advantage of the unrolled network structure, alternately using CNN for image denoising and maintaining data consistency in each iteration, reducing model parameters through weight sharing, achieving effective supervised learning.

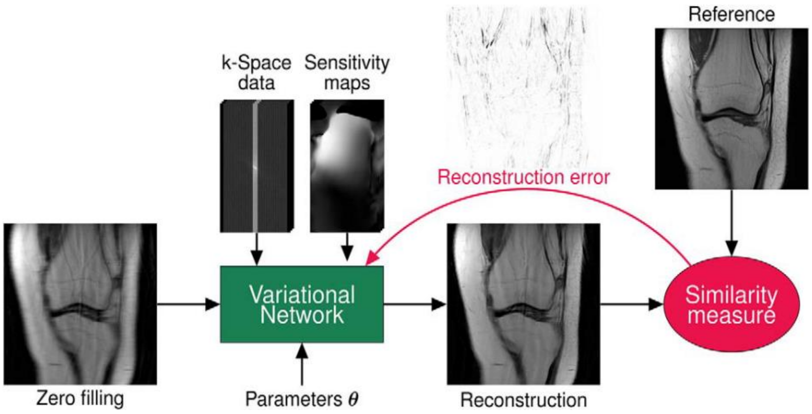

Figure 2: Supervised learning scheme[2]

Figure 2 shows the supervised learning scheme of VarNet, it iteratively implements a network that combines the mathematical structure of variational models with deep learning, compared with the reference image to update training parameters.

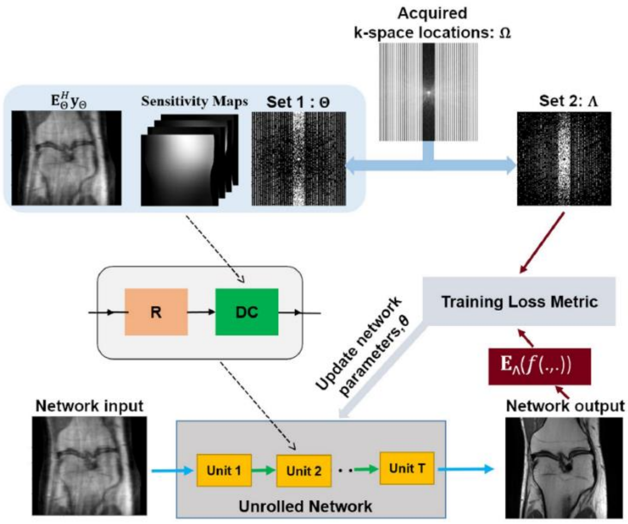

Figure 3: Self-supervised learning scheme[3]

Figure 3 shows the SSDU self-supervised architecture, which is proposed for MRI reconstruction without fully sampled data. It works by dividing the obtained k-space index into two disjoint sets Θ and Λ, where the former is used to enforce data consistency in the network and the latter is used to define the loss function for training.

2.3 Performance Evaluation

We used Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) as performance metrics to compare the similarity between the reconstructed images and the original fully sampled images. Training and testing of all methods were conducted on the same dataset to ensure a fair comparison.

3 Results

3.1 Test results

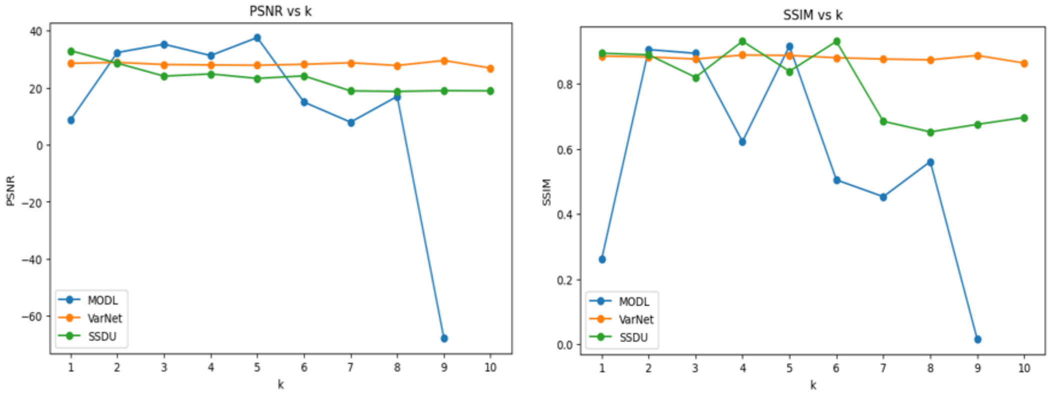

Figure 4: Test results within the 10 iterations, based on the same test datasets with undersampled folder 4.

Figure 4 shows the test results of the three modls. For MoDL, the best performance is achieved at the 5th iteration, with a PSNR of 37.55 dB and an SSIM of 0.89. However, beyond the 5th iteration, the model starts to overfit, resulting in a degradation of performance. On the other hand, VarNet exhibits stable performance across all 10 iterations and performs very well overall. However, for SSDU, the best results are obtained at the 5th iteration, with a slight decrease in performance observed beyond that point.

3.2 Trainable parameters

Since Both MoDL and SSDU are unrolled network and share the weights at each iteration, while VarNet doesnot share weights, its trainable variables numbers increase 100 times during the ten iterations. Thus, here we made a verify for MoDL and SSDU to check the performance under different structure complexities.

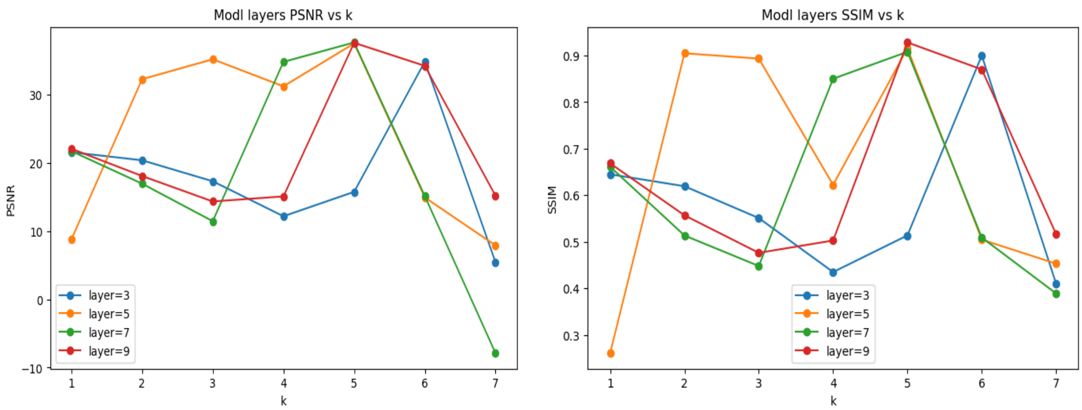

Figure 5: Test results of MoDL under different layer numbers.

Table 1 Test results under different layer numbers

Layers number	Test PSNR	Test SSIM	Total trainable parameters
3	15.78	0.51	39559
5	37.55	0.92	113,671
7	37.69	0.91	187,783
9	37.64	0.93	261,895

Figure 5 and Table 1 present the test results of Modl with varying numbers of training layers. It can be observed that the experiments with 9 layers achieve the best performance when the iteration is set to 5. However, it is evident that increasing the number of layers also leads to a corresponding increase in the number of trainable parameters, resulting in improved performance.

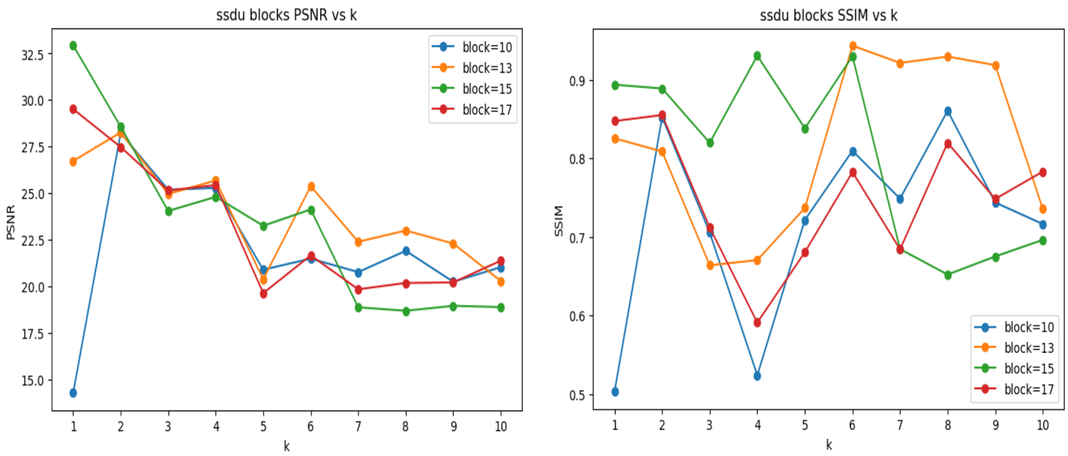

Figure 6: Test results of SSDU under different block numbers.

Table 2 Test results of SSDU under different block numbers

Blocks number	Test PSNR(dB)	Test SSIM	Total trainable parameters
11	21.48	0.81	814,787
13	25.38	0.94	962,499
15	24.13	0.93	1,110,211
17	21.66	0.78	1,257,923

Figure 6 and table 3 also show the test results of SSDU under different block numbers. The results from the four experiments clearly indicate that the best performance is achieved when the number of blocks is set to 13. And it also shows a worse performance when the number of blocks is set to more than 15.

3.3 Reconstruction results

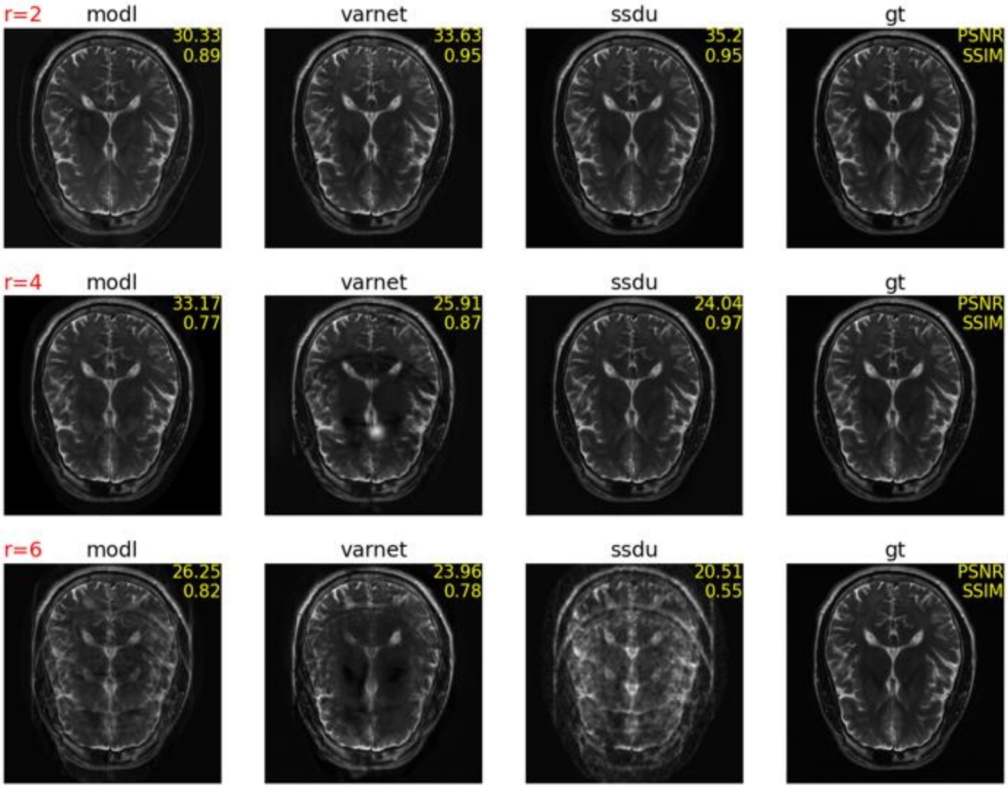

Figure 7: Reconstructed images with undersampled folders 2x, 4x and 6x.

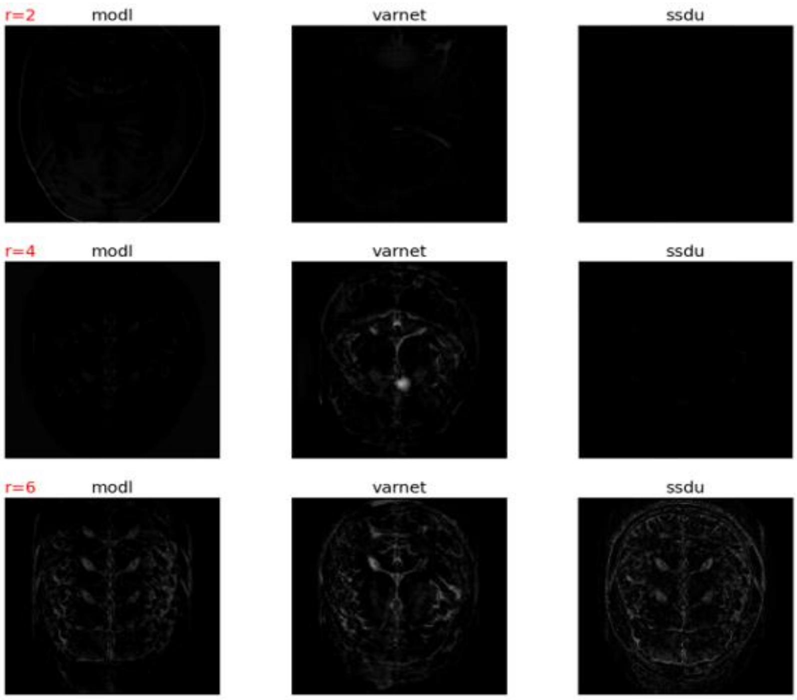

Figure 8: Image difference between reconstructed images and ground truth.

Figures 7 and 8 show the performance of the MRI reconstruction was quantitatively assessed using the PSNR and SSIM metrics across different undersampling factors (r=2, r=4, and r=6) under the same iteration.

The reconstruction quality was compared against ground truth (gt) images. And the reconstruction quality was inversely related to the undersampling factor across all methods tested. At a lower undersampling factor (r=2), the self-supervised deep learning method (SSDU) demonstrated superior performance with the highest PSNR and SSIM values, indicating its strength over supervised approaches in less challenging reconstruction scenarios.

As the undersampling factor increased (r=4 and r=6), a consistent degradation in image quality was evident, with all methods struggling to maintain fidelity to the ground truth. SSDU maintained a relative advantage at r=4, but its performance diminished significantly at r=6, underscoring the increasing difficulty in reconstruction tasks as the undersampling becomes more severe.

Overall, the results indicate that the reconstruction becomes more challenging with the increase of the undersampling factor, with more aliasing and artifacts occurring. While SSDU performed better at lower undersampling factors, supervised learning methods like MoDL and VarNet were more resilient at higher undersampling factors, indicating their potential in more demanding reconstruction scenarios.

3.4 Experiments on SSDU

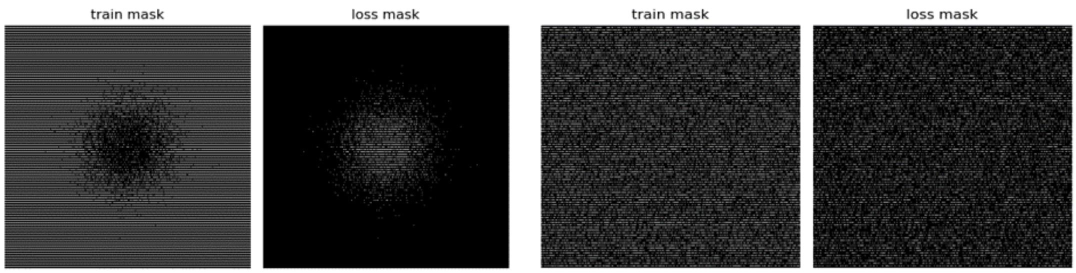

Figure 9: Gaussian selection(left) and Uniform selection masks(right).

Figure 9 shows the selection of the loss mask Λ, two strategies were examined: uniform random selection and variable-density Gaussian selection. In uniform random selection, the elements of Λ are randomly chosen from the acquired k-space data points (Ω). Conversely, the variable-density Gaussian selection applies a Gaussian distribution to weigh the selection process, thereby preferring the selection of certain k-space data points based on their location.

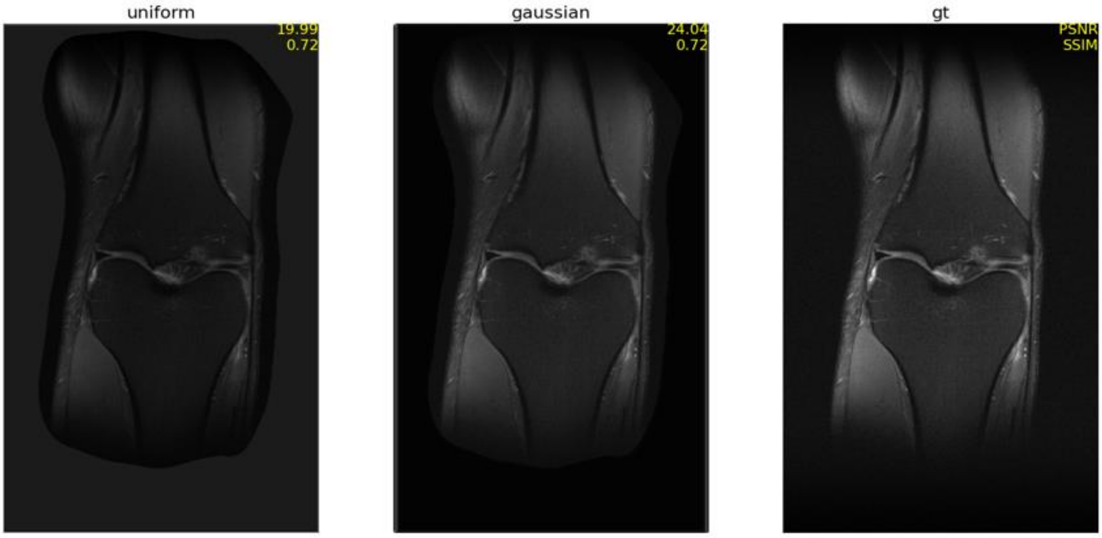

Figure 10: Comparison of Reconstruction Methods Using Gaussian and Uniform Subsampling Mask Selection

Figure 10 presents a side-by-side comparison of reconstruction results utilizing Gaussian and Uniform selection methods for undersampled points alongside the ground truth for reference. The Gaussian selection method demonstrates superior reconstruction quality, achieving a higher PSNR of 24.04 dB and maintaining a SSIM of 0.72, which is closer to the ground truth. In contrast, the Uniform selection method results in a lower PSNR of 19.99 dB and an equivalent SSIM of 0.72, indicating less accurate reconstruction. These quantitative metrics confirm that the Gaussian selection method is more effective than the Uniform method in preserving image fidelity in the context of MRI reconstruction because it gathers more k-space center information.

4 Discussion

This project embarked on an exploration of advanced MRI image reconstruction techniques, focusing on the comparative analysis of Supervised Learning approaches MoDL and VarNet, as well as a Self-Supervised Learning approach SSDU within the context of accelerated MRI imaging. Our findings underscore the nuanced performance landscapes these methodologies inhabit, accentuated by varying acceleration factors.

The MoDL and SSDU, leveraging unrolled network architectures with shared weights, demonstrated a remarkable balance between reconstruction quality and computational efficiency. Particularly, MoDL's performance peaked at intermediate layer configurations, suggesting an optimal balance between model complexity and overfitting risk. Conversely, SSDU's best results at a moderate block count highlight the technique's adeptness in harnessing self-supervised learning paradigms, albeit with diminishing returns beyond a certain block complexity threshold.

VarNet's consistency across iterations underscores its robustness but also hints at a potential computational and memory footprint challenge due to its non-shared weights approach. This factor becomes increasingly critical as we scale to larger datasets and more complex reconstruction tasks.

The influence of undersampling on reconstruction quality was profound across all methods, with higher undersampling factors invariably degrading performance. However, the differential degradation rates hint at inherent methodological strengths and weaknesses. SSDU's superior performance at lower undersampling rates (2x) demonstrates its potential in scenarios where minimal data loss is paramount, while MoDL and VarNet's resilience at higher undersampling rates (4x, 6x) suggests a robustness that may be more suited to demanding clinical applications.

The Gaussian versus uniform selection comparison further enriches our understanding of k-space data sampling's impact on reconstruction quality. The Gaussian method's superiority, particularly in the context of SSDU, reinforces the critical role of strategic data selection in optimizing reconstruction outcomes.

5 Conclusion

Our investigation into deep learning-based MRI image reconstruction methods reveals a complex interplay between methodological approaches, undersampling rates, and data selection strategies. MoDL and SSDU, with their unrolled network architectures and shared weights, offer a promising balance of efficiency and performance, particularly at lower to moderate levels of model complexity with a moderate CNN layer and Residual block quantity. VarNet stands out for its robust performance across a wider range of undersampling factors, albeit with greater computational demands.

The project highlights the critical impact of undersampling on reconstruction quality, with SSDU outperforming at lower rates, suggesting its suitability for applications where data conservation is crucial. In contrast, MoDL and VarNet's stronger performance under higher undersampling conditions points to their potential in more challenging clinical scenarios.

Moreover, the comparative analysis of Gaussian and uniform selection methods in SSDU underscores the importance of strategic k-space data sampling in maximizing reconstruction fidelity. The superiority of the Gaussian method in this context suggests a pathway to further optimize MRI reconstruction processes.

This project not only advances our understanding of the capabilities and limitations of current deep learning-based MRI reconstruction methods but also sets the stage for future innovations in this rapidly evolving field. Future studies could explore the integration of these methods with emerging deep learning models, investigate the impact of even higher undersampling rates, and delve into real-world clinical application scenarios to fully unleash the potential of accelerated MRI imaging.

References

[1]Aggarwal, H. K., Mani, M. P., & Jacob, M. (2019). MoDL: Model-based deep learning architecture for inverse problems. *IEEE Transactions on Medical Imaging, 38*(2), 394-405. DOI:10.1109/TMI.2018.2865356

[2] Hammernik, K., Klatzer, T., Kobler, E., Recht, M. P., Sodickson, D. K., Pock, T., & Knoll, F. (2018). Learning a Variational Network for Reconstruction of Accelerated MRI Data. *Magnetic Resonance in Medicine, 79*(3), 3055-3071. DOI:10.1002/mrm.26977

[3] Yaman, B., Hosseini, S. A. H., Moeller, S., Ellermann, J., Uğurbil, K., & Akçakaya, M. (2020). Self-supervised learning of physics-guided reconstruction neural networks without fully sampled reference data. *Magnetic Resonance in Medicine,* 84(6), 3172–3191. Doi:10.1002/mrm.28378