Project Report : CS 7643

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Abstract

MRI scans are a critical diagnostic tool but often require long acquisition times, limiting their use in time-sensitive medical scenarios. This project leverages deep learning to accelerate MRI reconstruction while maintaining diagnostic image quality. Focusing on knee scans, we implemented and fine-tuned neural networks, including U-Net and MRNet. A key innovation of our approach is a hybrid method that uses MRNet to generate heatmaps of regions of interest (ROIs), which are then used to upweigh the loss function for these ROIs in the U-Net model. This hybrid approach enhances the reconstruction quality by emphasizing important regions. We evaluated the models' performance using the fastMRI and kneeMRI datasets, focusing on both reconstruction quality and speed.

1. Introduction

1.1. Motivation

MRI scans play an essential role for non-invasive diagnostics, particularly for detecting knee joint conditions. However, existing methods for acquiring and reconstructing MRI scans are time intensive, posing challenges in time-sensitive situations like emergency diagnostics. Accelerating MRI reconstruction without compromising the quality of diagnosis and its accuracy is essential to improve patient outcomes as well as broadening its accessibility.

1.2. Current Practice and Limitations

Traditional MRI acceleration techniques such as SMASH, SENSE, and GRAPPA [2] rely on advance hardware and optimized sampling strategies. While effective to improve scan times, these traditional approaches struggle to reconstruct high-quality image when faced with highly under-sampled k-space data. Furthermore, the reliance on hardware upgrades makes them too expensive and inaccessible in resource-constrained settings.

1.3. Impact

By successfully developing an approached based on deep learning techniques to accelerate MRI reconstruction, we can address the limitations previously mentioned. This innovation has the potential to make high quality imaging more affordable and accessible, particularly in undeserved regions and emergency scenarios. Faster MRI reconstruction will reduce delays in diagnosis and enable proper and timely interventions during patient care.

1.4. Data Overview

This project leverages two high quality datasets for the model training and evaluation:

- **fastMRI dataset:** Provided by Facebook AI and NYU Langone [3], this dataset includes ground truth images and fully sampled k-space data, essential for training and validating the reconstruction model. The undersampled k-space data is created by applying a mask to the fully-sampled data and used as the input to train the model.
- **KneeMRI dataset:** Provided by Clinical Hospital Centre Rijeka, Croatia [4], this dataset focuses on knee injury detection, required for training the MRNet model and generating ROI heatmaps.

2. Approach

2.1. Implementation

We tacked the problem of accelerating MRI reconstruction using a deep learning approach. The primary architecture was a modified U-Net, adapted from the fastMRI repository. Our implementation includes:

- **UNet Architecture:** UNet follows an encoder-decoder structure with a bottleneck for feature transformation. The encoder extracts spatial features from the input undersampled k-space images using convolutional layers with ReLU activations, followed by max

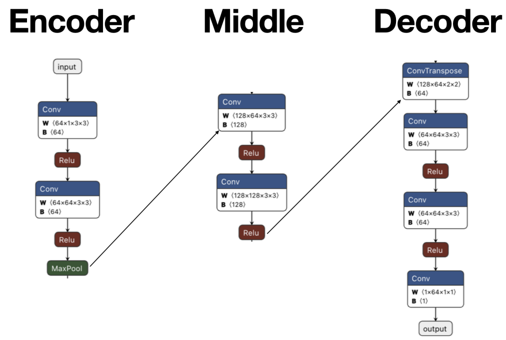

Figure 1. UNet Architecture

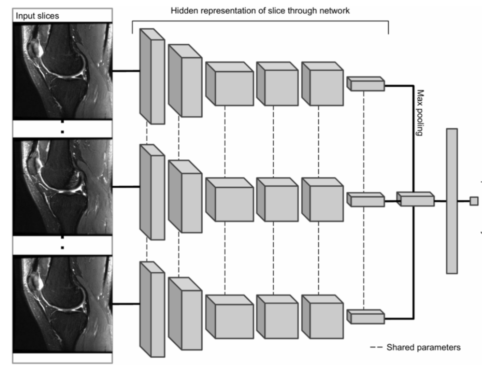

Figure 2. MRNet Architecture [1]

pooling to reduce dimensionality and capture contextual information. The middle block processes the compressed features to further refine the representation. The decoder upsamples the features through a transposed convolution layer and reconstructs the high-quality MRI image using additional convolutional layers, producing a single-channel output Figure 1. The model configuration and parameter details can be seen in Figure 3.

- **MRNet Architecture:** MRNet uses a modified version of AlexNet Figure 2. It extracts features from the MRI images through convolutional layers and processes them with a global average pooling (GAP) layer to reduce the spatial dimensions. The final features are passed through a linear layer to produce a single output, representing the likelihood of an abnormality [1]. The configuration and parameter details for MRNet are illustrated in Figure 4.

- **Undersampling of K-Space Data:** To speed up the MRI scan, we employed a undersampling strategy for k-space data, allowing the model to reconstruct high-quality images from fewer measurements. This undersampled k-space data is used to train the U-Net model.

- **ROI Identification:** While the primary model used the modified U-Net, we leveraged on the MRNet model to generate ROI heatmaps by utilizing Grad-CAM. This technique highlights important regions in an image by using the gradients of the target class flowing into the final convolutional layer of the MRNet.

- **Loss Function Adjustment:** As part of U-Net model training, We implemented a weighted mean squared error (MSE) loss function to upweigh the loss in the ROIs. With this approach, we can prioritize the reconstruction of the critical areas with better MRI quality.

```
=================================================================
Layer (type:depth-idx)                   Param #
=================================================================
├─Sequential: 1-1                        --
│    └─Sequential: 2-1                   --
│    │    └─Conv2d: 3-1                  640
│    │    └─ReLU: 3-2                    --
│    │    └─Conv2d: 3-3                  36,928
│    │    └─ReLU: 3-4                    --
│    └─MaxPool2d: 2-2                    --
├─Sequential: 1-2                        --
│    └─Conv2d: 2-3                       73,856
│    └─ReLU: 2-4                         --
│    └─Conv2d: 2-5                       147,584
│    └─ReLU: 2-6                         --
├─Sequential: 1-3                        --
│    └─ConvTranspose2d: 2-7              32,832
│    └─Sequential: 2-8                   --
│    │    └─Conv2d: 3-5                  36,928
│    │    └─ReLU: 3-6                    --
│    │    └─Conv2d: 3-7                  36,928
│    │    └─ReLU: 3-8                    --
│    └─Conv2d: 2-9                       65
=================================================================
Total params: 365,761
Trainable params: 365,761
Non-trainable params: 0
=================================================================
```

Figure 3. UNet: Model Configuration and Parameters

2.2. Challenges and Solutions

Anticipated challenges included handling undersampled data and ensuring high reconstruction fidelity. Early experiments with a smaller subset of the data revealed overfitting issues, which we mitigated through the use of a larger dataset and regularization techniques. Additionally, the extensive time and resource requirements for processing k-space and MRI image data posed significant obstacles. This challenge was resolved by utilizing GPUs from Google Colab and reducing the number of training epochs from 20 to 10. We also optimized hyperparameters such as learning rates and batch sizes to enhance performance.

2.3. Novelty

A key novelty of this approach is the use of an injury detection model to identify regions of interest (ROIs) and upweighing the MSE loss during the training of MRI reconstruction model to emphasize these critical areas. This innovative combination enhances reconstruction accuracy while

```
=================================================================
Layer (type:depth-idx)                   Param #
=================================================================
├─AlexNet: 1-1                           --
|    └─Sequential: 2-1                   --
|    |    └─Conv2d: 3-1                  23,296
|    |    └─ReLU: 3-2                    --
|    |    └─MaxPool2d: 3-3               --
|    |    └─Conv2d: 3-4                  307,392
|    |    └─ReLU: 3-5                    --
|    |    └─MaxPool2d: 3-6               --
|    |    └─Conv2d: 3-7                  663,936
|    |    └─ReLU: 3-8                    --
|    |    └─Conv2d: 3-9                  884,992
|    |    └─ReLU: 3-10                   --
|    |    └─Conv2d: 3-11                 590,080
|    |    └─ReLU: 3-12                   --
|    |    └─MaxPool2d: 3-13              --
|    └─AdaptiveAvgPool2d: 2-2            --
|    └─Sequential: 2-3                   --
|    |    └─Dropout: 3-14                --
|    |    └─Linear: 3-15                 37,752,832
|    |    └─ReLU: 3-16                   --
|    |    └─Dropout: 3-17                --
|    |    └─Linear: 3-18                 16,781,312
|    |    └─ReLU: 3-19                   --
|    |    └─Linear: 3-20                 4,097,000
├─AdaptiveAvgPool2d: 1-2                 --
├─Linear: 1-3                            257
=================================================================
Total params: 61,101,097
Trainable params: 61,101,097
Non-trainable params: 0
=================================================================
```

Figure 4. MRNet: Model Configuration and Parameters

maintaining computational efficiency. The technique can also be extended to other imaging applications, offering a valuable template for the medical imaging field.

3. Experiments and Results

3.1. Evaluation Method

The final MRI reconstruction model was evaluated using both quantitative and qualitative methods. Quantitatively, weighted MSE loss was tracked during training, validation, and testing to assess the model's reconstruction accuracy. Qualitatively, the reconstructed MRI images were compared with the ground truth images to evaluate their similarity, and error maps were analyzed to identify discrepancies between the reconstructed and target images, providing insights into the reconstruction performance.

The model was somewhat successful in its ability to reconstruct MRI images, but the results were not optimal. While the reconstructed images were generally similar to the ground truth, they were noticeably blurry and lacked high quality. The average weighted MSE loss during testing was 0.000012, which is relatively high compared to training and validation losses, indicating that the model's accuracy could be improved. Error maps revealed that the model struggled in complex regions, where fine details were not well captured.

The limitations in image quality and the high testing loss can be attributed to the simplicity of the model architecture and the limited training time. These factors suggest that the model's performance could be improved by using more sophisticated architectures and extending the training duration. Thus, while the model showed potential, further improvements are needed for better quality reconstructions.

3.2. Quantitative Results

To evaluate the performance of the MRI reconstruction model, we monitored the training and validation weighted MSE losses across ten epochs. The final loss values are summarized in Table 1, and the corresponding loss curves are visualized in Figure 5.

Training and Validation Loss The final model demonstrated consistent improvement during training, as indicated by the steadily decreasing training and validation losses. The final training loss converged to 1.07×10^{-6}, while the final validation loss reached 1.01×10^{-6}, showing minimal difference between the two. These results suggests that the model generalizes well to unseen validation data and does not exhibit evidence of overfitting.

Testing Loss The final testing loss achieved by the model was 1.2×10^{-5}, which is slightly higher than the training and validation losses of 1.07×10^{-6} and 1.01×10^{-6} , respectively. While this indicates a slight decrease in performance when applied to unseen test data, the low magnitude of the testing loss demonstrates that the model retains strong generalization capabilities. This result underscores the model's effectiveness in reconstructing MRI images from undersampled k-space data while maintaining diagnostic quality. However, the observed gap highlights potential areas for refinement, such as further optimization of the training process or exploration of more sophisticated architectures.

Loss Curves Analysis Figure 5 shows the progression of training and validation losses over the ten epochs. During the initial epochs, the training loss decreases rapidly, reflecting effective learning. The validation loss demonstrates a slight fluctuation in the early epochs but it manages to stabilize as training progresses. This behavior aligns with expectations for a robust model capable of generalizing to validation data.

Effectiveness of Loss metrics The low values for MSE (mean squared loss) achieved by the model indicate a high quality in the image reconstruction with minimal pixel differences between the outputs and ground truth images. While further quantitative and qualitative evaluation would help to confirm the results, the trends observed suggest strong performance. Future work might benefit from incorporating perceptual and structural metrics like SSIM (Structural similarity index measure) or PSNR (Peak signal to noise ratio) to provide a deeper analysis of the reconstruction quality and level of distortions.

Metric	Final Value
Training Loss	1.07×10^{-6}
Validation Loss	1.01×10^{-6}
Test Loss	1.2×10^{-5}

Table 1. Final Loss Values. Values are reported in scientific notation for clarity.

Figure 5. Training and Validation Loss Curves over Ten Epochs

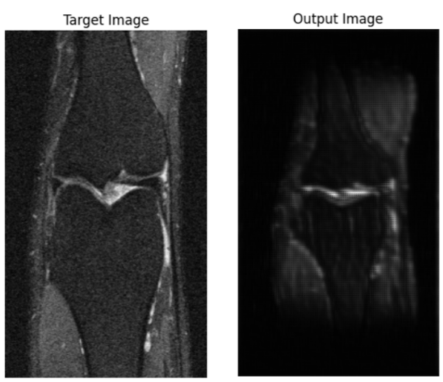

Figure 6. Ground Truth and Output Image Comparison

3.3. Qualitative Results

When the reconstructed images were visually inspected and compared to ground truth images, the results showed:

- The model was partially successful in reconstructing MRI images, but the results were suboptimal, with the images being blurry and lacking high quality despite resembling the ground truth Figure 6.

- The overlay of Grad-CAM heat maps demonstrated that the model focused on critical diagnostic areas most of the time which aligns with clinical priorities Figure 7.

- The error maps show brighter regions where the model struggles with critical areas, while darker regions indicate less important areas with smaller errors Figure 8.

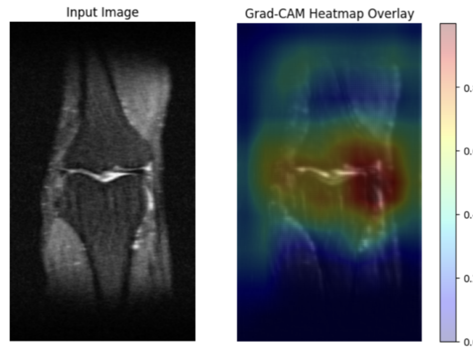

Figure 7. Input Image and HeatMap Analysis

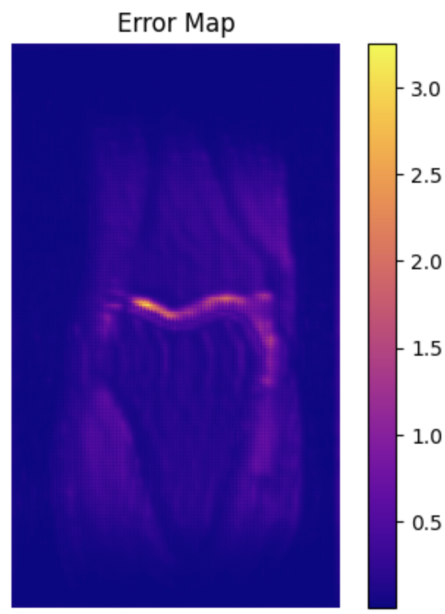

Figure 8. Error Map Example

This suggests the model needs improvement in reconstructing complex regions for better accuracy.

3.4. Code and Resources

- **Frameworks:** The implementation leveraged PyTorch[1], the fastMRI[2] repository [3], and .

- **Code Base:** The implementation is available as a supplementary material and can also be found at: GitHub

- **Datasets:** Utilized fastMRI knee dataset for reconstruction tasks and the KneeMRI dataset for validation of region of interest.

[1] Instructions to install PyTorch can be found here and documentation is available at the official site

[2] The fastMRI repository can be found here

4. Other Sections

4.1. Conclusions

In this project, we successfully applied deep learning techniques to accelerate MRI reconstruction from undersampled k-space data while maintaining diagnostic quality. The hybrid approach combined a modified U-Net for image reconstruction and MRNet for identifying regions of interest (ROIs) using Grad-CAM-generated heatmaps. By leveraging these ROIs, we implemented a weighted loss function that prioritized critical diagnostic areas during training, enhancing the reconstruction quality in key regions.

The results demonstrated the potential of this approach, with reconstructed images aligning closely with ground truth in many cases. Qualitative evaluations, including heatmap overlays, confirmed that the model effectively focused on diagnostically important areas. However, some limitations were observed, particularly in complex regions where fine details were not fully captured. Quantitative analysis also indicated that while the model performed well overall, improvements in reconstruction are needed for optimal results.

In addition, our project highlights the feasibility of integrating region-focused deep learning techniques in MRI reconstruction, showcasing significant advancements in both efficiency and diagnostic relevance.

4.1.1 Future Work

This study provides a strong foundation for accelerating MRI reconstruction using deep learning, but there is significant scope for further improvement. Future efforts could explore more complex medical imaging models with advanced architectures to enhance reconstruction fidelity, particularly in complex regions with fine details.

Another avenue for improvement lies in experimenting with different masking hyperparameters to find an optimal balance between undersampling k-space data and preserving high-quality reconstructed images. Fine-tuning these parameters could improve the model's ability to reconstruct critical diagnostic features while maintaining computational efficiency.

Increasing the amount and diversity of training data, particularly for the injury detection model, is also a priority. Enhanced ROI heatmaps generated from a more robust MRNet model could further refine the hybrid approach and improve reconstruction in diagnostically significant regions. Extending training time and incorporating more advanced data processing techniques could also help address limitations in the current implementation, resulting in higher reconstruction accuracy and better overall image quality.

Additionally, incorporating metrics such as Structural Similarity Index Measure (SSIM) and Peak Signal-to-Noise Ratio (PSNR) in the evaluation process could offer deeper insights into image quality. These metrics could serve as optimization targets to guide model improvements, helping to fine-tune performance and ensure that the reconstructed images are diagnostically reliable.

5. Work Division

Our team consists of 3 members: Fidel Morales, Minuk Lee, and Kyaw Htoon. Below are contributions of each team member:

- **Fidel Morales:** Fidel was responsible for preprocessing and loading the data, training the baseline model, optimizing the training code, and contributing to both the analysis and report writing.
- **Minuk Lee:** Minuk focused on fine-tuning the model by adjusting hyperparameters, visualizing results, creating evaluation metrics, and playing a key role in report writing.
- **Kyaw Htoon:** Kyaw implemented the hybrid approach, conducted experiments, analyzed the results, and created visualizations to support the findings. All three contributed significantly to the analysis and overall project execution.

References

[1] Nicholas Bien, Pranav Rajpurkar, Robyn L. Ball, Jeremy Irvin, Allison Park, Erik Jones, Michael Bereket, Bhavik N. Patel, Kristen W. Yeom, Katie Shpanskaya, Safwan Halabi, Evan Zucker, Gary Fanton, Derek F. Amanatullah, Christopher F. Beaulieu, Geoffrey M. Riley, Russell J. Stewart, Francis G. Blankenberg, David B. Larson, Ricky H. Jones, Curtis P. Langlotz, Andrew Y. Ng, and Matthew P. Lungren. Deep-learning-assisted diagnosis for knee magnetic resonance imaging: Development and retrospective validation of mrnet. *PLOS Medicine*, 15(11):e1002699, 2018. 2

[2] Matthias Mueller Robin M. Heidemann Mark A. Griswold Martin Blaimer, Felix Breuer and Peter M. Jakob. Smash, sense, pils, grappa how to choose the optimal method, 2004. 1

[3] Jure Zbontar, Florian Knoll, Anuroop Sriram, Matthew J. Muckley, Mary Bruno, Aaron Defazio, Marc Parente, Krzysztof J. Geras, Joe Katsnelson, Hersh Chandarana, Zizhao Zhang, Michal Drozdzal, Adriana Romero, Michael G. Rabbat, Pascal Vincent, James Pinkerton, Duo Wang, Nafissa Yakubova, Erich Owens, C. Lawrence Zitnick, Michael P. Recht, Daniel K. Sodickson, and Yvonne W. Lui. fastmri: An open dataset and benchmarks for accelerated MRI. *CoRR*, abs/1811.08839, 2018. 1, 4

[4] I. Štajduhar, M. Mamula, D. Miletić, and G. Unal. Semi-automated detection of anterior cruciate ligament injury from mri. Dataset, 2017. Computer Methods and Programs in Biomedicine, Volume 140, Pages 151–164. 1