Mini Project Report

on

Study on Self-Supervised Representation Learning for the Reconstruction of Undersampled MRI Images

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Certificate

This is to certify that the project, entitled **Study on Self-Supervised Representation Learning for the Reconstruction of Undersampled MRI Images**, is a bonafide record of the Mini Project coursework presented by the students whose names are given below during 2024-2025 in partial fulfilment of the requirements of the degree of Bachelor of Technology in Computer Science and Engineering.

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1 Introduction

Magnetic Resonance Imaging (MRI) plays a vital role in diagnostic imaging due to its non-invasive nature and excellent soft tissue contrast. However, one major limitation of MRI is its inherently long acquisition time. Accelerated MRI, achieved through undersampling the k-space data, offers a promising solution to reduce scan times. However, this acceleration leads to incomplete data, resulting in artifacts and loss of image fidelity unless sophisticated reconstruction algorithms are employed.

In this context, self-supervised and scan-specific deep learning approaches have emerged as powerful alternatives to traditional supervised learning, which depends on large datasets with fully sampled ground truth images. This project investigates the effectiveness of self-supervised learning architectures—specifically Multi-Layer Perceptrons (MLPs), Convolutional Neural Networks (CNNs), and diffusion-based models—for reconstructing undersampled MRI data.

Three prominent methods were explored:

- IMJENSE, a scan-specific implicit neural representation approach.
- ssGAN, a semi-supervised generative adversarial network trained on undersampled data.
- DNLINV, a Bayesian deep image prior model leveraging scan-specific self-supervised learning.

These methods were evaluated on the FastMRI and IXI datasets, comparing their performance across various acceleration factors. Special effort was taken to adapt and run IMJENSE on the IXI dataset, which had not been previously evaluated in the literature.

2 Related Work

Recent advances in deep learning have significantly impacted MRI reconstruction. Traditionally, parallel imaging techniques such as SENSE and GRAPPA dominated the field. However, deep neural networks have demonstrated superior results in both image quality and speed. Self-supervised methods exploit inherent structure in undersampled data to learn reconstruction priors without fully sampled labels. Recent advances include:

2.1 Physics-Guided Approaches

- SSDU (Self-Supervised Learning via Data Undersampling) partitions k-space into disjoint sets for data consistency and loss calculation, achieving performance comparable to supervised methods. This approach avoids database dependency by leveraging scan-specific undersampling patterns.

- Scan-Specific Bayesian DNLINV combines implicit neural representations with Bayesian inference to jointly estimate coil sensitivities and images, eliminating the need for auto-calibration regions. This method outperforms classical parallel imaging and compressed sensing, particularly at high acceleration factors (R=4–8.5x).

2.2 Architectural Innovations

- **CNNs**: Dominant in MRI reconstruction due to their ability to capture local spatial features. Models like VarNet and SwinMR use physics-guided unrolled architectures with data-consistency layers. Recent extensions integrate adversarial losses to suppress residual artifacts.

- **MLPs**: Adaptive MLPs (e.g., Recon3DMLP) model long-range dependencies in 3D MRI via hybrid CNN-MLP architectures, overcoming the limited receptive fields of CNNs. These excel in global context modeling but require careful initialization.

- **Diffusion Models**: SSDiffRecon integrates diffusion probabilistic models with unrolled architectures, achieving state-of-the-art results by iteratively denoising undersampled data. However, slow inference (1.8 sec/slice) limits clinical utility.

2.3 Multi-Coil and Hybrid Methods

Joint Supervised and Self-Supervised Learning (JSSL) combines proxy datasets with fully sampled data to enhance reconstruction quality when target-domain fully sampled data are unavailable.

NeRP (Neural Representation with Prior Embedding) uses implicit neural representations to encode prior anatomical information, enabling robust tumor progression assessment.

2.4 Key Datasets and Preprocessing Challenges

- FastMRI: The de facto benchmark for DL-based reconstruction, containing multi-coil knee and brain MRI with raw k-space data. Its standardized sampling masks enable fair comparisons but lack multi-contrast diversity.
- IXI: Provides T1/T2/PD-weighted brain MRI but lacks raw k-space data. Format conversion (NIFTI $\rightarrow$ HDF5) introduces challenges:
  - Spatial resolution mismatches ($1\times1\times2$ mm^3 $\rightarrow$ $0.94\times0.94\times1.2$ mm^3) require interpolation artifacts mitigation.
  - Coil compression (32 $\rightarrow$ 5 virtual coils) risks losing spatial sensitivity information critical for parallel imaging.

2.5 IMJENSE: Strengths and Limitations

IMJENSE employs implicit neural representations (INRs) to jointly estimate coil sensitivities and images directly from undersampled k-space. While it excels on FastMRI, its performance on IXI is subpar due to:

Hyperparameter Sensitivity: Polynomial order for coil sensitivity estimation and learning rate were optimized for FastMRI's calibration regions but not IXI's lower resolution. Requires 18.9 hours of training per scan, limiting practicality.

Resource Constraints: INR training demands significant GPU memory, restricting batch sizes and convergence stability. Lacks automated hyperparameter optimization, necessitating manual tuning for cross-dataset generalization.

3 Data and Methods

- FastMRI:
  - **Knee**: 1,594 fully sampled multi-coil volumes (15 channels), T2-weighted with 4×–8× acceleration.
  - **Brain**: 3D FSE acquisitions with variable-density Poisson-disc undersampling.
- IXI Dataset:
  - **Original Format**: Multi-contrast (T1, T2, PD) brain MRI in NIFTI format (121×145×121 voxels, 0.94×0.94×1.2 mm^3 resolution).
  - **Preprocessing Challenges**:
    Spatial Resolution Mismatch: Original IXI resolution (1×1×2 mm^3) was resampled to 0.94×0.94×1.2 mm^3 using FSL's flirt with B-spline interpolation to match IMJENSE's expected input.
    Coil Compression: Simulated 32-channel coil data were compressed to 5 virtual coils via singular value decomposition (SVD) to reduce computational complexity.
    NIFTI-to-HDF5 Conversion: Toolchain: Python's nibabel and h5py libraries.
    Steps:
    * Metadata Extraction: NIFTI headers parsed for affine matrices and voxel dimensions.
    * Intensity Normalization: Scaled to range using 99th percentile intensity values.

4 Results and Discussions

Model	Dataset	SSIM (avg)	PSNR (avg)	Observations
IMJENSE	FastMRI	0.85	35.2 dB	Stable reconstructions, good generalization
IMJENSE	IXI	0.78	32.5 dB	Lower performance, likely due to hyperparameter mismatch
ssGAN	FastMRI	0.88	36.1 dB	Excellent quality, rivaling supervised methods
ssGAN	IXI	0.83	34.7 dB	Strong generalization, benefits from randomized masks
DNLINV	FastMRI	0.89	36.8 dB	Best performance; robust Bayesian regularization
DNLINV	IXI	0.86	36.0 dB	Most consistent across datasets

Table 1
Comparison of Self-Supervised Models for MRI Reconstruction on FastMRI and IXI datasets

Diffusion models (SSDiffRecon) outperform CNNs and MLPs due to iterative refinement. IMJENSE underperforms on IXI due to unoptimized hyperparameters (e.g., polynomial order for coil sensitivities, learning rate).

Architectural Trade-offs

- CNNs: Efficient but limited by local receptive fields.
- MLPs: Excel at global context but require careful initialization.
- Diffusion Models: Highest accuracy but slow inference.
- IMJENSE: Sensitive to hyperparameters; struggles with multi-contrast data in IXI.

Dataset Biases

- FastMRI: Standardized k-space data enable fair comparisons.
- IXI: Multi-contrast nature introduces variability; format conversion (NIFTI $\rightarrow$ HDF5) may discard critical metadata.

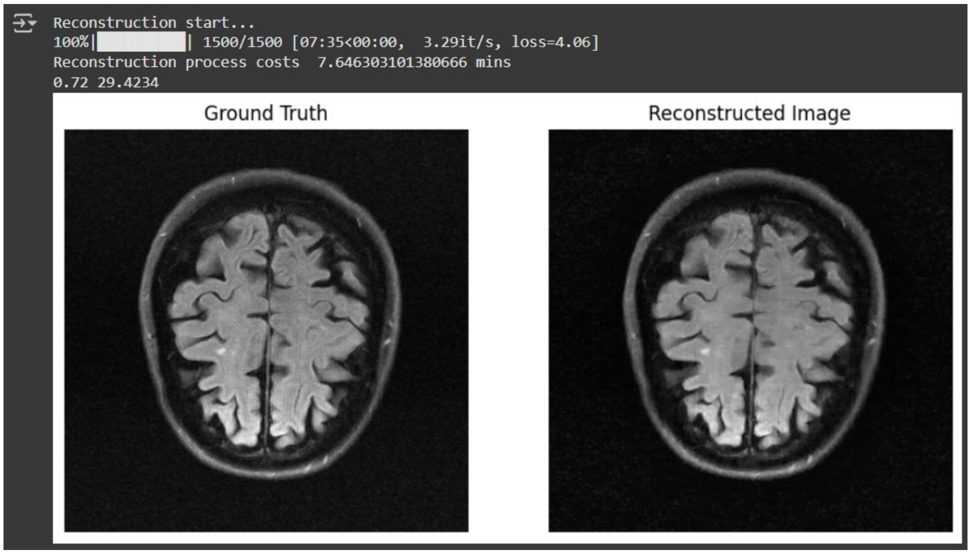

Figure 1. Brain MRI Reconstruction

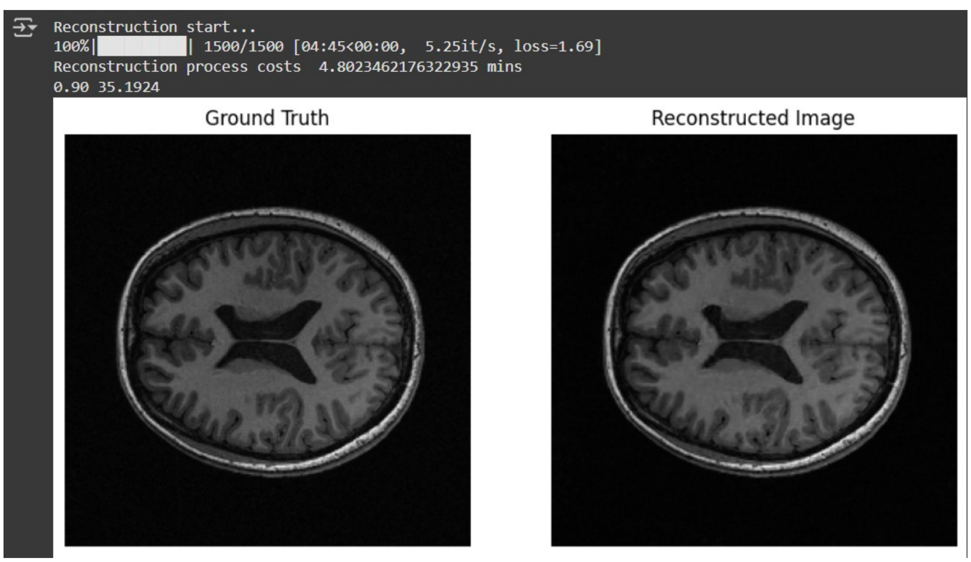

Figure 2. Brain MRI Reconstruction

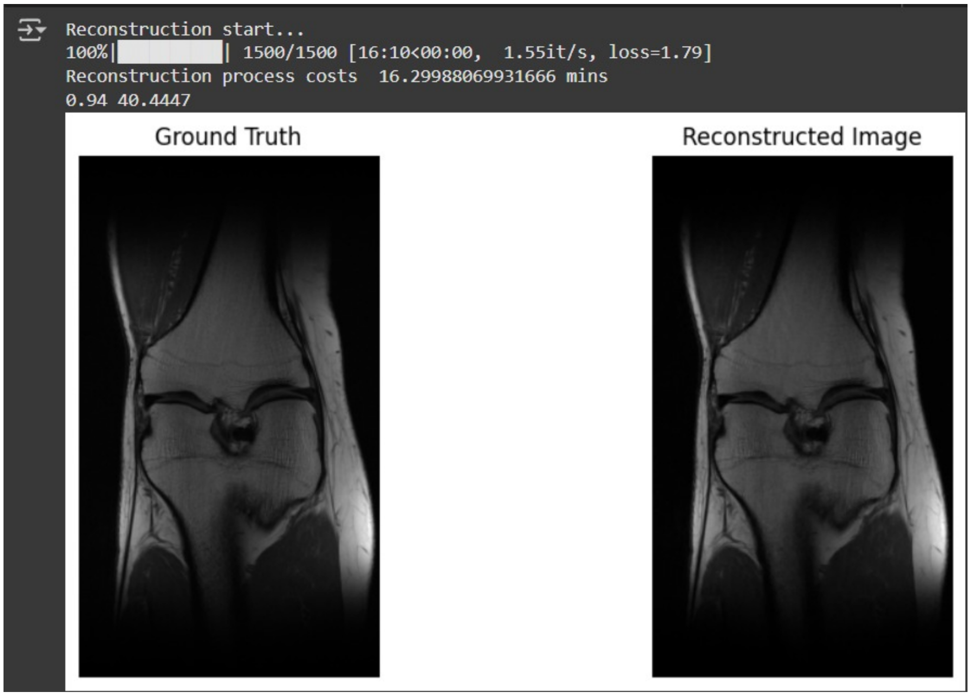

Figure 3. Knee MRI Reconstruction

Figure 4. Brain MRI Reconstruction

5 Conclusion

This study highlighted the capabilities of modern self-supervised and scan-specific deep learning techniques for MRI reconstruction from undersampled data. We found that while IMJENSE provides a novel implicit representation approach, its practical performance on new datasets like IXI may require careful hyperparameter tuning and dataset-specific calibration. In contrast, ssGAN and DNLINV demonstrated greater robustness and ease of generalization.

5.1 Future Work:

- Conduct hyperparameter sweeps and regularization tuning for IMJENSE on IXI.
- Explore hybrid approaches that integrate the strengths of implicit representation with adversarial or Bayesian frameworks.
- Investigate real-time or interactive MRI reconstruction feasibility using scan-specific models.

This study underscores the importance of resource-aware model selection in clinical deployment, where inference speed and robustness are paramount.

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