

---

## fastMRI



[Website](#) | [Dataset](#) | [GitHub](#) | [Publications](#)

Accelerating Magnetic Resonance Imaging (MRI) by acquiring fewer measurements has the potential to reduce medical costs, minimize stress to patients and make MR imaging possible in applications where it is currently prohibitively slow or expensive.

fastMRI is a collaborative research project from Facebook AI Research (FAIR) and NYU Langone Health to investigate the use of AI to make MRI scans faster. NYU Langone Health has released fully anonymized knee and brain MRI datasets that can be downloaded from the fastMRI dataset page. Publications associated with the fastMRI project can be found at the end of this README.

This repository contains convenient PyTorch data loaders, subsampling functions, evaluation metrics, and reference implementations of simple baseline methods. It also contains implementations for methods in some of the publications of the fastMRI project.

## Documentation

### The fastMRI Dataset

There are multiple publications describing different subcomponents of the data (e.g., brain vs. knee) and associated baselines. All of the fastMRI data can be downloaded from the fastMRI dataset page.

- **Project Summary, Datasets, Baselines:** fastMRI: An Open Dataset and Benchmarks for Accelerated MRI ({J. Zbontar, F. Knoll, A. Sriram\*} et al., 2018)
- **Knee Data:** fastMRI: A Publicly Available Raw k-Space and DICOM Dataset of Knee Images for Accelerated MR Image Reconstruction Using Machine Learning ({F. Knoll, J. Zbontar} et al., 2020)
- **Brain Dataset Properties:** Supplemental Material of Results of the 2020 fastMRI Challenge for Machine Learning MR Image Reconstruction ({M. Muckley, B. Riemenschneider} et al., 2021)
- **Prostate Data:** FastMRI Prostate: A Publicly Available, Biparametric MRI Dataset to Advance Machine Learning for Prostate Cancer Imaging (Tibrewala et al., 2023)

## Code Repository

For code documentation, most functions and classes have accompanying docstrings that you can access via the `help` function in IPython. For example:

---

```
1 from fastmri.data import SliceDataset
2
3 help(SliceDataset)
```

## Dependencies and Installation

**Note:** Contributions to the code are continuously tested via GitHub actions. If you encounter an issue, the best first thing to do is to try to match the `tests` environment in `setup.cfg`, e.g., `pip install --editable ".[tests]"` when installing from source.

**Note:** As documented in Issue 215, there is currently a memory leak when using `h5py` installed from `pip` and converting to a `torch.Tensor`. To avoid the leak, you need to use `h5py` with a version of HDF5 before 1.12.1. As of February 16, 2022, the `conda` version of `h5py` 3.6.0 used HDF5 1.10.6, which avoids the leak.

First install PyTorch according to the directions at the PyTorch Website for your operating system and CUDA setup. Then, run

```
1 pip install fastmri
```

`pip` will handle all package dependencies. After this you should be able to run most of the code in the repository.

## Installing Directly from Source

If you want to install directly from the GitHub source, clone the repository, navigate to the `fastmri` root directory and run

```
1 pip install -e .
```

## Package Structure & Usage

The repository is centered around the `fastmri` module. The following breaks down the basic structure:

`fastmri`: Contains a number of basic tools for complex number math, coil combinations, etc.

- `fastmri.data`: Contains data utility functions from original `data` folder that can be used to create sampling masks and submission files.
- `fastmri.models`: Contains reconstruction models, such as the U-Net and VarNet.
- `fastmri.pl_modules`: PyTorch Lightning modules for data loading, training, and logging.

---

## Examples and Reproducibility

The `fastmri_examples` and `banding_removal` folders include code for reproducibility. The baseline models were used in the arXiv paper.

A brief summary of implementations based on papers with links to code follows. For completeness we also mention work on active acquisition, which is hosted in another repository.

- **Baseline Models**

- Zero-filled examples for saving images for leaderboard submission
- ESPIRiT—an eigenvalue approach to autocalibrating parallel MRI: where SENSE meets GRAPPA (M. Uecker et al., 2013)
- U-Net: Convolutional networks for biomedical image segmentation (O. Ronneberger et al., 2015)

- **Sampling, Reconstruction and Artifact Correction**

- Offset Sampling Improves Deep Learning based Accelerated MRI Reconstructions by Exploiting Symmetry (A. Defazio, 2019)
- End-to-End Variational Networks for Accelerated MRI Reconstruction ({A. Sriram, J. Zbontar} et al., 2020)
- MRI Banding Removal via Adversarial Training (A. Defazio, et al., 2020)
- Deep Learning Reconstruction Enables Prospectively Accelerated Clinical Knee MRI (P. Johnson et al., 2023)

- **Active Acquisition**

- (external repository) Reducing uncertainty in undersampled MRI reconstruction with active acquisition (Z. Zhang et al., 2019)
- (external repository) Active MR k-space Sampling with Reinforcement Learning (L. Pineda et al., 2020)
- On learning adaptive acquisition policies for undersampled multi-coil MRI reconstruction (T. Bakker et al., 2022)

- **Prostate Data**

- (external repository) FastMRI Prostate: A Publicly Available, Biparametric MRI Dataset to Advance Machine Learning for Prostate Cancer Imaging (Tibrewala et al., 2023)

---

## Testing

Run `pytest tests`. By default integration tests that use the fastMRI data are skipped. If you would like to run these tests, set `SKIP_INTEGRATIONS` to `False` in the `conftest`.

## Training a model

The data README has a bare-bones example for how to load data and incorporate data transforms. This jupyter notebook contains a simple tutorial explaining how to get started working with the data.

Please look at this U-Net demo script for an example of how to train a model using the PyTorch Lightning framework.

## Submitting to the Leaderboard

**NOTICE:** As documented in Discussion 293, the `fastmri.org` domain was transferred from Meta ownership to NYU ownership on 2023-04-17, and NYU has not yet rebuilt the site. Until the site and leaderboards are rebuilt by NYU, leaderboards will be unavailable. Mitigations are presented in Discussion 293.

## License

fastMRI is MIT licensed, as found in the LICENSE file.

## Cite

If you use the fastMRI data or code in your project, please cite the arXiv paper:

```
1 @misc{zbontar2018fastMRI,
2   title={{fastMRI}: An Open Dataset and Benchmarks for Accelerated {
3     MRI}},
4   author={Jure Zbontar and Florian Knoll and Anuroop Sriram and
5     Tullie Murrell and Zhengnan Huang and Matthew J. Muckley and
6     Aaron Defazio and Ruben Stern and Patricia Johnson and Mary
7     Bruno and Marc Parente and Krzysztof J. Geras and Joe Katsnelson
8     and Hersh Chandarana and Zizhao Zhang and Michal Drozdal and
9     Adriana Romero and Michael Rabbat and Pascal Vincent and Nafissa
10    Yakubova and James Pinkerton and Duo Wang and Erich Owens and C
11    . Lawrence Zitnick and Michael P. Recht and Daniel K. Sodickson
12    and Yvonne W. Lui},
```

---

```
4   journal = {ArXiv e-prints},
5   archivePrefix = "arXiv",
6   eprint = {1811.08839},
7   year={2018}
8 }
```

If you use the fastMRI prostate data or code in your project, please cite that paper:

```
1 @misc{tibrewala2023fastmri,
2   title={{FastMRI Prostate}: A Publicly Available, Biparametric {MRI}
3     Dataset to Advance Machine Learning for Prostate Cancer Imaging},
4   author={Tibrewala, Radhika and Dutt, Tarun and Tong, Angela and
5     Ginocchio, Luke and Keerthivasan, Mahesh B and Baete, Steven H and
6     Chopra, Sumit and Lui, Yvonne W and Sodickson, Daniel K and
7     Chandarana, Hersh and Johnson, Patricia M},
8   journal = {ArXiv e-prints},
9   archivePrefix = "arXiv",
10  eprint={2304.09254},
11  year={2023}
12 }
```

## List of Papers

The following lists titles of papers from the fastMRI project. The corresponding abstracts, as well as links to preprints and code can be found [here](#).

1. Zbontar, J\*, Knoll, F\*, Sriram, A\*, Murrell, T., Huang, Z., Muckley, M. J., ... & Lui, Y. W. (2018). fastMRI: An Open Dataset and Benchmarks for Accelerated MRI. *arXiv preprint arXiv:1811.08839*.
2. Zhang, Z., Romero, A., Muckley, M. J., Vincent, P., Yang, L., & Drozdal, M. (2019). Reducing uncertainty in undersampled MRI reconstruction with active acquisition. In *CVPR*, pages 2049-2058.
3. Defazio, A. (2019). Offset Sampling Improves Deep Learning based Accelerated MRI Reconstructions by Exploiting Symmetry. *arXiv preprint, arXiv:1912.01101*.
4. Knoll, F\*, Zbontar, J\*, Sriram, A., Muckley, M. J., Bruno, M., Defazio, A., ... & Lui, Y. W. (2020). fastMRI: A Publicly Available Raw k-Space and DICOM Dataset of Knee Images for Accelerated MR Image Reconstruction Using Machine Learning. *Radiology: Artificial Intelligence*, 2(1), page e190007.
5. Knoll, F\*, Murrell, T\*, Sriram, A\*, Yakubova, N., Zbontar, J., Rabbat, M., ... & Recht, M. P. (2020). Advancing machine learning for MR image reconstruction with an open competition: Overview of the 2019 fastMRI challenge. *Magnetic Resonance in Medicine*, 84(6), pages 3054-3070.
6. Sriram, A., Zbontar, J., Murrell, T., Zitnick, C. L., Defazio, A., & Sodickson, D. K. (2020). GrappaNet: Combining parallel imaging with deep learning for multi-coil MRI reconstruction. In *CVPR*, pages 14315-14322.

- 
7. Recht, M. P., Zbontar, J., Sodickson, D. K., Knoll, F., Yakubova, N., Sriram, A., ... & Zitnick, C. L. (2020). Using Deep Learning to Accelerate Knee MRI at 3T: Results of an Interchangeability Study. *American Journal of Roentgenology*, 215(6), pages 1421-1429.
  8. Pineda, L., Basu, S., Romero, A., Calandra, R., & Drozdal, M. (2020). Active MR k-space Sampling with Reinforcement Learning. In *MICCAI*, pages 23-33.
  9. Sriram, A.\*, Zbontar, J.\*, Murrell, T., Defazio, A., Zitnick, C. L., Yakubova, N., ... & Johnson, P. (2020). End-to-End Variational Networks for Accelerated MRI Reconstruction. In *MICCAI*, pages 64-73.
  10. Defazio, A., Murrell, T., & Recht, M. P. (2020). MRI Banding Removal via Adversarial Training. In *Advances in Neural Information Processing Systems*, 33, pages 7660-7670.
  11. Muckley, M. J.\*, Riemenschneider, B.\*, Radmanesh, A., Kim, S., Jeong, G., Ko, J., ... & Knoll, F. (2021). Results of the 2020 fastMRI Challenge for Machine Learning MR Image Reconstruction. *IEEE Transactions on Medical Imaging*, 40(9), pages 2306-2317.
  12. Johnson, P. M., Jeong, G., Hammernik, K., Schlemper, J., Qin, C., Duan, J., ..., & Knoll, F. (2021). Evaluation of the Robustness of Learned MR Image Reconstruction to Systematic Deviations Between Training and Test Data for the Models from the fastMRI Challenge. In *MICCAI MLMIR Workshop*, pages 25–34,
  13. Bakker, T., Muckley, M.J., Romero-Soriano, A., Drozdal, M. & Pineda, L. (2022). On learning adaptive acquisition policies for undersampled multi-coil MRI reconstruction. In *MIDL*, pages 63-85.
  14. Radmanesh, A.\*, Muckley, M. J.\*, Murrell, T., Lindsey, E., Sriram, A., Knoll, F., ... & Lui, Y. W. (2022). Exploring the Acceleration Limits of Deep Learning VarNet-based Two-dimensional Brain MRI. *Radiology: Artificial Intelligence*, 4(6), page e210313.
  15. Johnson, P.M., Lin, D.J., Zbontar, J., Zitnick, C.L., Sriram, A., Muckley, M., Babb, J.S., Kline, M., Ciavarra, G., Alaia, E., ..., & Knoll, F. (2023). Deep Learning Reconstruction Enables Prospectively Accelerated Clinical Knee MRI. *Radiology*, 307(2), page e220425.
  16. Tibrewala, R., Dutt, T., Tong, A., Ginocchio, L., Keerthivasan, M.B., Baete, S.H., Lui, Y.W., Sodickson, D.K., Chandarana, H., Johnson, P.M. (2023). FastMRI Prostate: A Publicly Available, Biparametric MRI Dataset to Advance Machine Learning for Prostate Cancer Imaging. *arXiv preprint, arXiv:2034.09254*.