




Fetpype: An Open-Source Pipeline for Reproducible Fetal Brain MRI Analysis

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Summary

Fetal brain Magnetic Resonance Imaging (MRI) is crucial for assessing neurodevelopment *in utero*. However, analyzing this data presents significant challenges due to fetal motion, low signal-to-noise ratio, and the need for complex multi-step processing, including motion correction, super-resolution reconstruction, segmentation, and surface extraction. While various specialized tools exist for individual steps, integrating them into robust, reproducible, and user-friendly workflows that go from raw images to processed volumes is not straightforward. This lack of standardization hinders reproducibility across studies and limits the adoption of advanced analysis techniques for researchers and clinicians. To address these challenges, we introduce Fetpype, an open-source Python library designed to streamline and standardize the preprocessing and analysis of T2-weighted fetal brain MRI data as illustrated in ([Figure 1](#)).

Statement of need

Fetpype is a Python package integrating several established neuroimaging software principles and tools to create a cohesive and extensible framework, which we summarize in four points.

1. **Data Standardization:** Fetpype expects input data organized according to the Brain Imaging Data Structure (BIDS) standard ([Gorgolewski et al., 2016](#)), promoting interoperability and simplifying data management.
2. **Containerization:** Individual processing tools are encapsulated within Docker or Singularity containers. This ensures reproducibility and reduces installation issues, providing a better experience for the end user.
3. **Workflow Management:** The Nipype library ([Gorgolewski et al., 2011](#)) is used to construct processing workflows: it provides a robust interface for combining different steps from different containers or packages, facilitating data caching and parallelization, and allowing pipelines to be easily shareable.
4. **Configuration:** Pipeline configuration is managed using simple YAML files and the Hydra library ([Yadan, 2019](#)), allowing users to easily select between different modules or parameters without directly modifying the code. The current implementation of Fetpype integrates modules for:
 - a. **Data preprocessing:** including brain extraction using Fetal-BET ([Faghihpouryesh et al., 2024](#)), non-local means denoising ([Manjón et al., 2010](#)) and N4 bias-field correction ([Tustison et al., 2010](#)), all wrapped into a single container built at https://github.com/fetpype/utlis_container,

- b. **Super-resolution reconstruction:** implementing three widely used pipelines: NeSVoR (Xu et al., 2023), SVRTK (Kuklisova-Murgasova et al., 2012; Alena U. Uus et al., 2022), and NiftyMIC (Ebner et al., 2020),
- c. **Segmentation:** implementing BOUNTI (Alena U. Uus et al., 2023) and the developing human connectome project pipeline (Makropoulos et al., 2018) and
- d. **Cortical surface extraction:** using a custom implementation available at https://github.com/fetpype/surface_processing based on (Bazin & Pham, 2005, 2007; Ma et al., 2022).

The objective underlying the conceptualization of Fetpype is to provide the fetal MRI community with a standardized, reproducible, and flexible open-source platform for preprocessing and analysis. By providing a modular Nipype-based framework, it facilitates the integration of custom community tools through containerized interfaces and clear contribution guidelines. Fetpype aims to advance research by improving comparability across studies and fostering community collaboration by facilitating the dissemination of new image processing methods for clinical applications. The pipeline is publicly available on GitHub (<https://github.com/fetpype/fetpype>).

In the future, we plan to supplement Fetpype with an automated reporting library containing automated quality control (Sanchez et al., 2026, 2024), subject-wise and population-wise biometry and volumetry (Esteban et al., 2017; Neves Silva et al., 2025), as well as spectral analysis of surfaces (Germanaud et al., 2012). We welcome contributions of authors desiring to integrate their method to Fetpype.

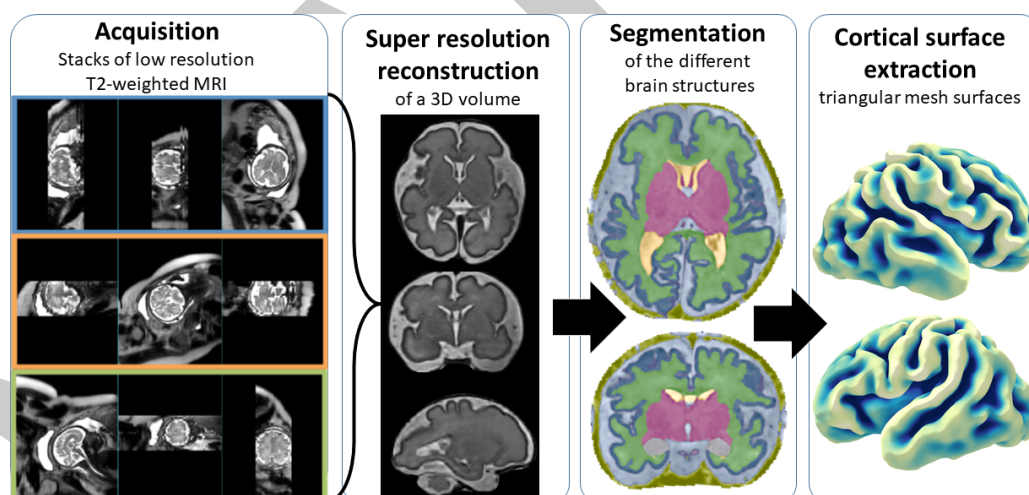


Figure 1: The different steps covered by Fetpype. Starting from several T2-weighted stacks of thick slices of the fetal brain (*acquisition*), Fetpype pre-processes data before feeding them to a *super-resolution reconstruction* algorithm that fuses them in a single high-resolution volume. This volume then undergoes *segmentation*, before moving to *cortical surface extraction*.

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