

# MedImages.jl: A Julia Package for Handling Medical Imaging Data and Spatial Metadata

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## Abstract

Medical image analysis requires specialized tools that can handle not only high-dimensional voxel data but also critical spatial metadata such as origin, spacing, and orientation. While established libraries exist in languages like Python and C++, the Julia programming language offers a unique opportunity to solve the "two-language problem" by providing high-level productivity with low-level performance. In this article, we introduce MedImages.jl, an open-source Julia package designed to facilitate the loading, saving, processing, and resampling of medical images while rigorously maintaining spatial consistency. We discuss how Julia helps in scientific computing, the specific challenges of medical imaging formats, and how open-source libraries like MedImages.jl boost researcher productivity by democratizing access to complex image processing tasks. We also provide code examples demonstrating the package's capabilities in handling spatial metadata and performing transformations.

*Keywords:* Medical Imaging, Julia, Open Source, Spatial Metadata, DICOM, NIfTI

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## 1. Introduction

Scientific computing has traditionally suffered from the "two-language problem," where researchers prototype in high-level languages like Python, R, or MATLAB for productivity but must rewrite performance-critical sections in low-level languages like C or Fortran [? ? ]. This dual-language approach expands the required expertise, necessitates frequent code reimplementations, and reduces code reusability and productivity [? ? ]. Julia is a high-level, dynamic programming language specifically designed to bridge this gap [?

9 ]. It combines the ease of use of scripting languages with the performance  
10 of compiled languages, making it an ideal candidate for computationally  
11 intensive fields like medical imaging [? ].

12 In the domain of medical imaging, the need for high performance is  
13 paramount. Tasks such as 3D image reconstruction, registration, and seg-  
14 mentation involve processing massive datasets with complex algorithms. Ju-  
15 lia’s ability to run native code on both CPUs and GPUs, combined with  
16 automatic differentiation support, makes it an excellent platform for this  
17 research [? ].

18 In this article, we present MedImages.jl, a Julia package that leverages  
19 these advantages to provide a robust framework for handling medical im-  
20 ages. We address several key questions: How does Julia help in scientific  
21 computing? What is its potential for medical image analysis? What are  
22 the difficulties related to medical imaging formats? And how do open-source  
23 tools boost productivity?

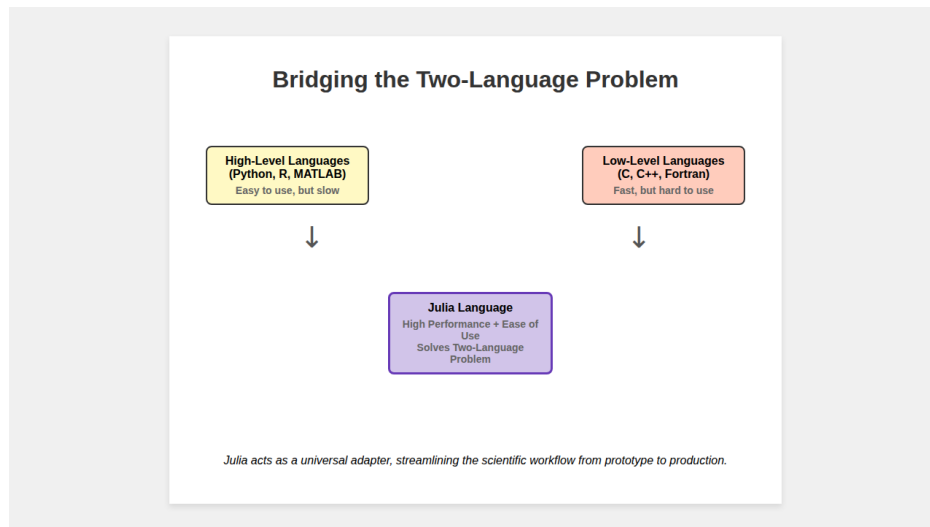


Figure 1: Julia bridges the gap between high-level productivity languages and low-level performance languages, solving the two-language problem in scientific computing. It acts as a universal adapter, streamlining the scientific workflow from prototype to production.

## 24 2. Julia in Scientific Computing

25 Julia helps researchers and developers by providing a robust, high-performance  
26 environment suitable for a wide range of scientific and technical computing

27 needs [? ]. Its competitive edge stems from its Just-In-Time (JIT) compiler,  
28 which generates efficient machine code comparable to C/C++ [? ].

## 29 2.1. Key Features and Performance

- 30 • **Multiple Dispatch:** This powerful, central paradigm allows functions  
31 to be customized based on the specific types of arguments they receive  
32 [? ]. This enables generic, high-performance code where the compiler  
33 can optimize function calls based on run-time types [? ].
- 34 • **Parallel and Distributed Computing:** Julia has built-in support  
35 for distributed and parallel computing, simplifying the distribution of  
36 calculations across multiple cores or machines [? ]. This is critical for  
37 large-scale data analysis and High-Performance Computing (HPC) [?  
38 ].
- 39 • **Interoperability:** It can call functions and libraries written in C,  
40 Fortran, and Python with little or no overhead [? ]. Packages like  
41 PyCall.jl and RCall.jl provide transparent interfaces for calling code  
42 between Julia and Python or R [? ].
- 43 • **Metaprogramming:** Julia allows programmatic construction and ma-  
44 nipulation of expressions as first-class values, aiding in creating and  
45 analyzing syntactically sound expressions [? ].

## 46 2.2. Problem Solving: The Expression Problem

47 Julia addresses the "Expression Problem," a core challenge in software  
48 design relating to extensibility and compatibility. This problem occurs when  
49 a user needs to add new data types or new operations to a system while  
50 maintaining compatibility with existing code [? ]. Julia's architecture, un-  
51 derpinned by multiple dispatch, solves this by allowing developers to add new  
52 functions to existing data types and new data types that seamlessly integrate  
53 with existing algorithms without modifying the original code [? ].

## 54 3. Potential for Julia in Medical Imaging

55 Julia presents significant potential for transforming the analysis and pro-  
56 cessing of medical images, primarily by combining high performance with  
57 developer productivity and leveraging specialized toolsets that address com-  
58 putational bottlenecks inherent in complex medical imaging modalities.

### 59 3.1. Novel Packages and Frameworks

60 Julia’s ecosystem includes specialized packages that enable end-to-end  
61 medical image processing workflows and offer high-performance alternatives  
62 to established frameworks.

- 63 • **MRIReco.jl**: An open-source, flexible, and high-performance MRI  
64 reconstruction framework implemented entirely in Julia [? ]. It of-  
65 fers functionality for basic MR simulation and iterative reconstruction,  
66 achieving speeds comparable to highly optimized C/C++ libraries [?  
67 ].
- 68 • **KomaMRI.jl**: This framework enables general MRI simulations with  
69 robust GPU acceleration [? ]. Its speed and flexibility make complex  
70 MR simulations more accessible for research and education [? ].
- 71 • **BlochSimulators.jl**: A GPU-compatible Bloch simulation toolbox  
72 that surpasses existing toolboxes in static, compiled languages [? ].

### 73 3.2. Accelerating Quantitative Imaging

74 The computational speed of Julia makes advanced parameter estimation  
75 feasible for clinical use. For instance, a Julia-based toolkit for Selective Inver-  
76 sion Recovery (SIR) MRI parameter estimation showed a 20-fold reduction  
77 in computational time compared to a previous MATLAB implementation [?  
78 ]. When fitting an entire human brain, Julia was approximately 90x faster  
79 than MATLAB’s single-threaded operation [? ]. This drastic reduction in  
80 computational cost is critical for making advanced quantitative MRI (qMRI)  
81 parameters accessible in clinical settings.

## 82 4. Challenges in Medical Imaging Formats

83 Medical imaging formats, particularly DICOM, present significant diffi-  
84 culties for researchers. The core challenges relate to the complexity of the  
85 standard and the handling of spatial metadata.



## 103 4.2. Format Complexity and DICOM

104 The DICOM standard is ubiquitous but notoriously complex. It specifies  
105 Information Object Definitions (IODs) and services for communication, mak-  
106 ing adoption difficult for many researchers [? ]. Even when using high-level  
107 libraries, accessing spatial metadata can be error-prone due to the highly  
108 nested structure of annotations [? ]. Researchers often convert DICOM  
109 objects into simpler alternative formats (like NIFTI) for analysis, but this  
110 conversion risks losing important contextual information [? ? ].

## 111 5. MedImages.jl: Software Description

112 MedImages.jl is developed to address these challenges within the Julia  
113 ecosystem. It provides a standardized structure for storing and manipulating  
114 medical image data and metadata, similar in philosophy to SimpleITK but  
115 leveraging Julia’s native capabilities.

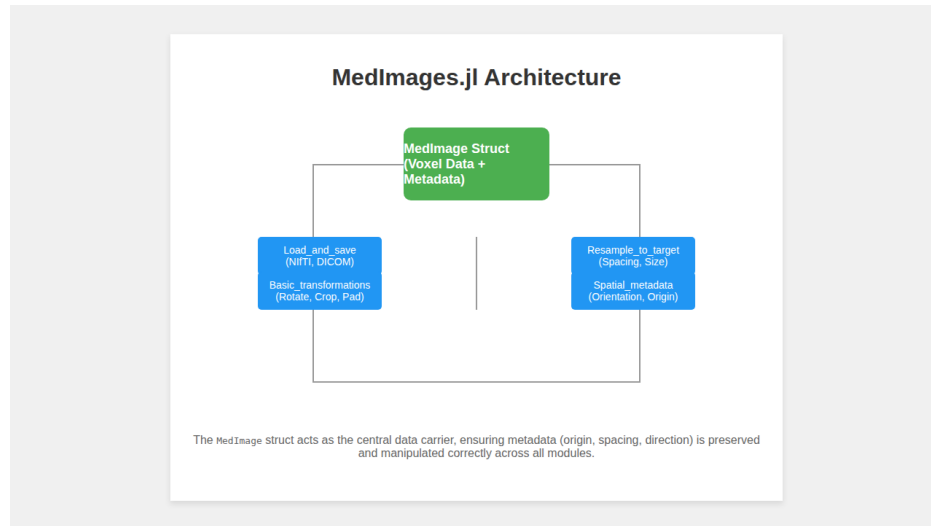


Figure 3: Architecture of MedImages.jl. The **MedImage** struct is central, supporting various modules for loading, resampling, transforming, and spatial metadata handling. The modular design allows for easy extension.

### 116 5.1. Architecture

117 The core of the package is the **MedImage** struct, which rigorously encapsu-  
118 lates both the image data and its spatial context:

- 119 • `voxel_data`: The multidimensional array of pixel values (e.g., 512x512x3).
- 120 • `origin`: Tuple of 3 Float64 values indicating the origin.
- 121 • `spacing`: Tuple of 3 Float64 values indicating voxel spacing.
- 122 • `direction`: 9-element tuple of Float64 values for orientation cosines.
- 123 • `image_type`, `image_subtype`: Enums for modality (MRI, CT, PET)
- 124 and subtype (T1, T2, FLAIR, etc.).
- 125 • `patient_uid`, `study_uid`, `series_uid`: UUIDs for data management.

## 126 5.2. Key Functionalities and Usage

### 127 5.2.1. Loading and Saving

128 MedImages.jl supports reading and writing standard formats, ensuring  
 129 metadata is preserved. The `Load_and_save` module handles the intricacies  
 130 of file I/O.

```
131 using MedImages
132
133
134 # Load an image from a NIfTI file
135 img = load_med_image("brain_scan.nii")
136
137 # Access metadata
138 println("Spacing: ", img.spacing)
139 println("Origin: ", img.origin)
140 println("Direction: ", img.direction)
141
```

Listing 1: Loading a medical image

### 142 5.2.2. Resampling

143 The `Resample_to_target` module allows images to be resampled to a new  
 144 geometry (spacing, size, orientation). This is a critical step for registering  
 145 images from different sources or modalities, where pixel-to-pixel correspon-  
 146 dence is not guaranteed [? ].

```
147 # Define target spacing (e.g., isotropic 1mm)
148 new_spacing = (1.0, 1.0, 1.0)
149
150
151 # Resample using linear interpolation
152 resampled_img = resample_to_spacing(img, new_spacing,
153     Interpolator_enum.Linear_en)
154
```

Listing 2: Resampling an image to a new spacing

### 155 5.2.3. Spatial Metadata Manipulation

156 The `Spatial_metadata_change` module provides tools to change orientation and spacing explicitly, ensuring the physical reference frame is maintained. This adheres to the "Physical Space Tenet" [? ], where the image is defined by its physical occupation rather than just its array indices.

```
160 # Change orientation to Right-Posterior-Inferior (RPI)
161 # This handles the permutation of axes and direction cosines
162 reoriented_img = change_orientation(img, Orientation_code.
163 ORIENTATION_RPI)
```

Listing 3: Changing image orientation

### 166 5.2.4. Basic Transformations

167 Common image processing operations like rotation, cropping, and padding are handled by the `Basic_transformations` module. These operations are aware of the spatial metadata, updating the origin and direction as needed.

## 170 6. Democratizing Access through Open Source

171 Open-source libraries like MedImages.jl, SimpleITK, and MONAI play a crucial role in democratizing access to medical image processing by lowering barriers to entry.

### 174 6.1. Boosting Productivity

175 Open-source toolkits serve as high-level abstraction layers that hide the intricate, low-level details of core medical imaging standards and algorithms [? ]. By abstracting the complexities of DICOM parsing and spatial math, these tools allow researchers to focus on algorithmic innovation rather than boilerplate code. For example, SimpleITK provides a simplified interface to ITK, making powerful algorithms accessible via Python or R [? ]. MedImages.jl brings similar benefits to the Julia community, enabling rapid prototyping without sacrificing performance.

### 183 6.2. Enhancing Reproducibility and Collaboration

184 Standardized open-source tools ensure reproducibility, a foundational pillar of scientific integrity [? ]. When researchers use a common framework for handling metadata, they avoid common pitfalls like coordinate system mismatch. Tools like highdicom ensure that ML model outputs are encoded



188 in standardized DICOM formats, facilitating clinical integration [? ]. Open-  
189 source projects also foster vibrant communities where code and knowledge  
190 are freely exchanged, leading to continuous evolution and enhancement of  
191 the software [? ].

## 192 7. Discussion and Future Work

193 MedImages.jl fills a critical gap in the Julia ecosystem by providing a  
194 native, high-performance tool for medical image manipulation. While wrap-  
195 pers for ITK exist, a pure Julia implementation offers better integration with  
196 other Julia packages, such as ‘DifferentialEquations.jl’ or ‘Flux.jl’, allowing  
197 for end-to-end differentiable pipelines.

198 One of the key advantages of MedImages.jl is its lightweight nature com-  
199 pared to heavy dependencies like ITK. By implementing core functionali-  
200 ties in native Julia, it allows for easier deployment and faster precompila-  
201 tion times. Furthermore, the potential for GPU acceleration using Julia’s  
202 ‘CUDA.jl’ or ‘AMDGPU.jl’ packages is a significant area for future devel-  
203 opment. The ‘MedImage’ struct is designed with this in mind, with a ‘cur-  
204 rent\_device’ field to track where the data resides.

205 Future work will focus on:

- 206 • **GPU Integration:** Fully leveraging Julia’s GPU capabilities for re-  
207 sampling and transformation operations.
- 208 • **Advanced Registration:** Implementing intensity-based registration  
209 algorithms natively in Julia.
- 210 • **Deep Learning Integration:** Creating seamless bridges to ‘Flux.jl’  
211 and ‘Lux.jl’ for medical image segmentation and reconstruction tasks.

## 212 8. Conclusion

213 MedImages.jl represents a significant step towards a robust medical imag-  
214 ing ecosystem in Julia. By solving the two-language problem, handling com-  
215 plex spatial metadata correctly, and adhering to open-source principles, it  
216 empowers researchers to build high-performance, reproducible, and clinically  
217 relevant imaging pipelines. As the Julia ecosystem grows, tools like Med-  
218 Images.jl will be instrumental in unlocking the full potential of this modern  
219 language for medical science, enabling faster transition from research to clin-  
220 ical deployment.

## 221 Acknowledgements

222 We acknowledge the Julia community and the developers of ITK and  
223 SimpleITK for their pioneering work in defining standards for medical image  
224 analysis.

## 225 References

- 226 [1] S. Pal, M. Bhattacharya, S. Dash, S.-S. Lee, C. Chakraborty, A next-  
227 generation dynamic programming language julia: Its features and appli-  
228 cations in biological science, *Journal of Advanced Research* 64 (10 2024).  
229 doi:10.1016/j.jare.2023.11.015.  
230 URL <http://dx.doi.org/10.1016/j.jare.2023.11.015>
- 231 [2] J. Belyakova, B. Chung, J. Gelinas, J. Nash, R. Tate, J. Vitek, World age  
232 in julia: Optimizing method dispatch in the presence of eval (extended  
233 version), *arXiv* (2020). doi:10.48550/ARXIV.2010.07516.  
234 URL <https://arxiv.org/abs/2010.07516>
- 235 [3] N. J. Sisco, P. Wang, A. M. Stokes, R. D. Dortch, Rapid parameter  
236 estimation for selective inversion recovery myelin imaging using an open-  
237 source julia toolkit, *PeerJ* 10 (3 2022). doi:10.7717/peerj.13043.  
238 URL <http://dx.doi.org/10.7717/peerj.13043>
- 239 [4] S. Ahn, S. G. Ross, E. Asma, J. Miao, X. Jin, L. Cheng, S. D. Wol-  
240 lenweber, R. M. Manjeshwar, Quantitative comparison of osem and pe-  
241 nalized likelihood image reconstruction using relative difference penal-  
242 ties for clinical pet, *Physics in Medicine and Biology* 60 (7 2015).  
243 doi:10.1088/0031-9155/60/15/5733.  
244 URL <http://dx.doi.org/10.1088/0031-9155/60/15/5733>
- 245 [5] J. Eschle, T. Gál, M. Giordano, P. Gras, B. Hegner, L. Heinrich, U. H.  
246 Acosta, S. Kluth, J. Ling, P. Mato, M. Mikhasenko, A. M. Briceño,  
247 J. Pivarski, K. Samaras-Tsakiris, O. Schulz, G. A. Stewart, J. Strube,  
248 V. Vassilev, Potential of the julia programming language for high energy  
249 physics computing, *Computing and Software for Big Science* 7 (10 2023).  
250 doi:10.1007/s41781-023-00104-x.  
251 URL <http://dx.doi.org/10.1007/s41781-023-00104-x>

- 252 [6] N. J. Sisco, P. Wang, A. Stokes, R. Dortch, Rapid parameter estimation  
253 for selective inversion recovery myelin imaging using an open-source julia  
254 toolkit (9 2021). doi:10.1101/2021.09.27.461996.  
255 URL <http://dx.doi.org/10.1101/2021.09.27.461996>
- 256 [7] T. Knopp, M. Grosser, Mrireco.jl: An mri reconstruction framework  
257 written in julia, arXiv (2021). doi:10.48550/ARXIV.2101.12624.  
258 URL <https://arxiv.org/abs/2101.12624>
- 259 [8] E. Roesch, J. G. Greener, A. L. MacLean, H. Nassar, C. Rackauckas,  
260 T. E. Holy, M. P. H. Stumpf, Julia for biologists, Nature Methods 20 (4  
261 2023). doi:10.1038/s41592-023-01832-z.  
262 URL <http://dx.doi.org/10.1038/s41592-023-01832-z>
- 263 [9] O. van der Heide, C. A. T. van den Berg, A. Sbrizzi, Gpu-accelerated  
264 bloch simulations and mr-stat reconstructions using the julia program-  
265 ming language, Magnetic Resonance in Medicine 92 (3 2024). doi:  
266 10.1002/mrm.30074.  
267 URL <http://dx.doi.org/10.1002/mrm.30074>
- 268 [10] Z. Yaniv, B. C. Lowekamp, H. J. Johnson, R. Beare, Simpleitk image-  
269 analysis notebooks: a collaborative environment for education and re-  
270 producible research, Journal of Digital Imaging 31 (11 2017). doi:  
271 10.1007/s10278-017-0037-8.  
272 URL <http://dx.doi.org/10.1007/s10278-017-0037-8>
- 273 [11] R. Beare, B. Lowekamp, Z. Yaniv, Image segmentation, registration  
274 and characterization in *r* with **simpleitk**, Journal of  
275 Statistical Software 86 (2018). doi:10.18637/jss.v086.i08.  
276 URL <http://dx.doi.org/10.18637/jss.v086.i08>
- 277 [12] C. P. Bridge, C. Gorman, S. Pieper, S. W. Doyle, J. K. Lennerz,  
278 J. Kalpathy-Cramer, D. A. Clunie, A. Y. Fedorov, M. D. Herrmann,  
279 Highdicom: a python library for standardized encoding of image an-  
280 notations and machine learning model outputs in pathology and ra-  
281 diology, Journal of Digital Imaging 35 (8 2022). doi:10.1007/  
282 s10278-022-00683-y.  
283 URL <http://dx.doi.org/10.1007/s10278-022-00683-y>

- 284 [13] R. Sandkühler, C. Jud, S. Andermatt, P. C. Cattin, Airlab: Autograd  
285 image registration laboratory, arXiv (2018). doi:10.48550/ARXIV.  
286 1806.09907.  
287 URL <https://arxiv.org/abs/1806.09907>
- 288 [14] B. C. Lowekamp, D. T. Chen, L. Ibáñez, D. Blezek, The design of sim-  
289 pleitk, Frontiers in Neuroinformatics 7 (2013). doi:10.3389/fninf.  
290 2013.00045.  
291 URL <http://dx.doi.org/10.3389/fninf.2013.00045>