JMI Journal of Medical Imaging

EDITORIAL

Toward Continued Growth for the JMI Community

Dear JMI Community,

It is my pleasure to welcome you to JMI Issue 1 of Volume 12 (2025). We are off to a strong start, featuring articles ranging from the physics of medical imaging to image processing; from computer-aided diagnosis to image perception, observer performance, and technology assessment; and from biomedical applications in molecular, structural, and functional imaging (on the cover: "Backscattering Mueller matrix polarimetry estimates microscale anisotropy and orientation in complex brain tissue structure" by R. Carlson et al.) to digital pathology. I would like to extend my sincere thanks to the 330 extremely generous reviewers who dedicated their time and expertise to creating Volume 11 (2024). Many of these scientists reviewed multiple articles and multiple revisions, with our top contributor providing 7 reviews! THANK YOU ALL!

I am often asked how to volunteer as a reviewer or editor for JMI. SPIE is a nonprofit, volunteer-centric organization. Efforts to make our community stronger, more resilient, and more impactful are always welcome. A great way to get involved is publishing in JMI, attending SPIE conferences, and engaging with the program committees of the SPIE Medical Imaging sub-conferences. A highlight of my academic year is attending the SPIE Medical Imaging conference (this year in San Diego for February 2025) where I can engage with and learn from our peers in person.

For this editorial, I would like to take a step back and explain a critical decision step in the review process for JMI. After an author submits manuscript through our portal, it first undergoes a series of quality assurance, formatting, and integrity checks conducted by our dedicated SPIE staff. Once these are completed, the manuscript enters a workflow where a handling editor assess whether a manuscript aligns with the journal's scope and meets scientific rigor standards. We must make difficult decisions about whether to send a manuscript out to an associate editor or perform a desk reject. When evaluating papers, my key question is: *What can we learn from this work?*

A common challenge in evaluation arises when methods are developed using proprietary or private data, making reproducibility difficult. For instance, if the code cannot be shared due to commercialization or proprietary restrictions, or if the comparative technology is inaccessible, it is challenging to provide a fair and transparent evaluation. To address this, I *strongly* recommend that authors consider leveraging publicly available datasets. These can be used for secondary, ancillary, or supplementary experiments to demonstrate broader applicability beyond a single proprietary dataset. If private data must be used, authors should provide direct comparisons to existing published algorithms or methods in the field.

A frequent misconception is that simply listing previously published results on similar datasets constitutes a valid comparison. Variations in dataset difficulty, training/testing splits, and other factors mean that such tables do not provide a reliable quantitative basis for evaluating performance. Instead, if an author presents results comparing different algorithms, they must clearly document how these were obtained—whether sourced from prior work, re-implemented, or run independently. This level of transparency ensures an effective review process. If authors feel that this level of detail is ancillary, it can be included in an appendix or supplementary materials, but it should be readily accessible for review.

As many of you know, I am an enthusiastic advocate for academic challenges, competitions, and open datasets for algorithm benchmarking. Many excellent articles in JMI have leveraged such resources. However, when using challenge datasets, it is critical that authors explicitly state where the data originated and how the leaderboard rankings were determined. Too often, submissions fail to cite the challenge dataset properly, making interpretation difficult. If authors use challenge data and leaderboards, I strongly advise providing precise citations, including a DOI reference. If concerns arise about a platform's long-term accessibility, services exist to create an archival snapshot, such as a PDF of a webpage or a digitally signed access record, ensuring that leaderboard rankings remain verifiable. Establishing traceable and reproducible benchmarks is essential, particularly when a challenge evaluation platform is central to the assessment of an algorithm's performance.

We are excited about the continued growth of the JMI community. As authors prepare manuscripts for JMI, I urge careful documentation of the validity of the work in a way that facilitates the peer review process. Thoughtful manuscript preparation will save authors time, lead to more accurate reviews, reduce administrative burden for our editorial team, and lead to an efficient (and rapid) review process.

I look forward to continuing our work with our community in the upcoming issues of JMI.

Best wishes,
Bennett A. Landman
Editor in Chief

P.S. Remember that disclosure of artificial intelligence (AI)/Large Language Models (LLMs) is critical to transparency. Use of AI/LLM is not a problem, but lack of disclosure is a big problem. From the perspective of authors, reviewers, editors, and administrators, these tools let us do amazing things, but just like all tools in science, we need to state how they were used. For example: *This editorial was dictated with Otter.ai, reformatted with ChatGPT 4o, and reviewed and edited by me.*