

1 Introduction to Special Issue on Datasets hosted in
2 The Cancer Imaging Archive (TCIA)

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47 **Introduction**

48

49 Public datasets play a key role in enabling the medical research community to validate and build
50 upon each other works using data acquired outside of their home institutions. This is especially
51 critical for stimulating studies utilizing quantitative data analysis (radiomics) or artificial
52 intelligence/machine learning (AI/ML) approaches, for which validation and generalizability on
53 independent external cohorts are essential for acceptance and future clinical translation.
54 Recognizing this fact, the Journal of Medical Physics has introduced a new category of article
55 submissions known as *Medical Physics Dataset Articles* (MPDAs)¹. MPDAs help facilitate the
56 use of valuable open-access datasets by granting authors the opportunity to publish detailed
57 scientific or clinical descriptions of their data with unique digital object identifiers (DOIs) for
58 future citations. Unlike traditional manuscripts, these articles would focus on reproducibility and
59 the dataset's potential use cases and details of how it was acquired, curated, and published.

60

61 This special issue was organized in partnership with The Cancer Imaging Archive (TCIA)². TCIA
62 is an official image repository of the National Cancer Institute (NCI), and the preferred digital
63 repository for sharing cancer-related datasets described by the MPDA readership³. Its mission is
64 to provide proper de-identification and hosting services to relieve individual researchers of the
65 legal and technical complexities of sharing patient datasets. Image datasets are organized as
66 “collections”; typically focused on a common disease (e.g., lung cancer), image modality (MRI,
67 CT, digital histopathology, etc.) or research focus (e.g., quantitative imaging). TCIA is currently
68 home to 126 datasets⁴ collected as part of numerous NCI-funded clinical trials and data sharing
69 initiatives^{5,6} as well as datasets proposed by investigators in the broader research community⁷.

70

71 In many cases the submitter(s) of TCIA datasets may include radiology or pathology annotations,
72 image classifications, segmentations, radiomics features, or derived/reprocessed images.
73 However, there are often cases where those who access the data on TCIA may perform their own
74 analyses, which can result in additional image labels. In order to further support the enrichment
75 of existing datasets with these additional labels, TCIA has begun accepting proposals for third
76 party “Analysis Results” based on existing image collections. Sharing such analyses is critical,
77 not only to enhancing medical studies reproducibility and reusability, but also to providing
78 significant value to the data science community in the form of labeled image sets for training new
79 AI/ML algorithms and other automated analysis approaches. Currently TCIA contains 28 such
80 datasets⁸ several of which were submitted in relation to this special issue.

81

82 The aim of this special issue is to highlight valuable examples of MPDAs and publicly available
83 datasets that can be reused for future research endeavors and utilized for addressing emerging
84 scientific or clinical questions.

85

86 In “Head and neck cancer patient images for determining auto-segmentation accuracy in T2-
87 weighted magnetic resonance imaging through expert manual segmentations” by Cardenas, et al.⁹
88 describe a T2-weighted MRI dataset of 55 head and neck cancer patients that can be used to
89 evaluate the accuracy of auto-segmentation systems delineating organs at risk (OAR) through
90 comparisons to expert manual segmentations. The dataset can further complement existing CT

91 datasets, where MR soft tissue discrimination can further aid results for treatment planning, for
92 instance.

93
94 In “FAIR-compliant clinical, radiomics and DICOM metadata of RIDER, Interobserver, Lung1
95 and Head-Neck1 TCIA collections” by Kalendralis, et al.¹⁰ describe updated clinical data,
96 radiomics features and Digital Imaging and Communications in Medicine (DICOM) headers from
97 4 datasets analyzed as part of their Nature Communications radiomics study¹¹ in order to support
98 repeatability, reproducibility, generalizability and transparency in radiomics research, which can
99 be used as useful benchmark for future CT radiomics studies.

100
101 In “DICOM Re-encoding of Volumetrically Annotated Lung Imaging Data Consortium (LIDC)
102 Nodules” by Fedorov, et al.¹² describe annotations for lung nodules from 875 of the subjects
103 collected by the Lung Imaging Data Consortium and Image Database Resource Initiative (LIDC)
104 converted into standard DICOM objects to simplify reuse of the data with the readily available
105 open-source tools, and to improve adherence to FAIR (Findable, Accessible, Interoperable,
106 Reusable) principles¹³.

107
108 In “PleThora: Pleural effusion and thoracic cavity segmentations in diseased lungs for
109 benchmarking chest CT processing pipelines” by Kiser, et al.¹⁴ describe a dataset of thoracic cavity
110 segmentations and discrete pleural effusion segmentations annotated on 402 CT scans acquired
111 from patients with non-small cell lung cancer (NSCLC). These data can be used for developing
112 image analysis pipelines such as lung structure segmentation, lesion detection, and radiomics
113 feature extraction. Combining these pleural effusion segmentations with the gross tumor volume
114 segmentations already available from the “NSCLC Radiomics” dataset, which will also enable
115 investigation of radiomics profile differences between effusion and primary tumors.

116
117 In “Reproducibility analysis of multi-institutional paired expert annotations and radiomic features
118 of the Ivy Glioblastoma Atlas Project (Ivy GAP) dataset” by Pati, et al.¹⁵ describe their analyses
119 and resulting data from 31 IvyGAP subjects including multi-institutional expert annotations for
120 tumor sub-compartments, radiomic features, and the associated reproducibility meta-analysis to

121 facilitate developing image-based biomarkers for prognostic/predictive applications in patients
122 with glioblastoma.

123
124 In “CT images with expert manual contours of thoracic cancer for benchmarking auto-
125 segmentation accuracy” by Yang, et al.¹⁶ describe a well-curated computed tomography (CT)
126 dataset of high-quality manually drawn contours from 60 patients with thoracic cancer that can be
127 used to evaluate the accuracy of thoracic normal tissue auto-segmentation systems.

128
129 In “MRQy: An Open-Source Tool for Quality Control of MR Imaging Data” by Sadri, et al.¹⁷
130 describe how they used MRQy, an open-source quality control tool to analyze TCIA collections
131 with data that was submitted from multiple sites. The results can be used for: (a) interrogating
132 MRI cohorts for site- or equipment-based differences, and (b) quantifying the impact of MRI
133 artifacts on relative image quality. This information can help determine how to correct for these
134 variations prior to model development and assess future harmonization techniques.

135
136 In summary, this special issue and its related datasets will serve as a valuable resource to help
137 develop benchmarks for a wide variety of imaging applications including image processing,
138 quality assurance, diagnostic, prognostic, and radiomics approaches using rich, annotated CT
139 and/or MR datasets. This will further strengthen the value of these datasets, their utility and
140 potential impact in the field of medical physics with the overarching goal of encouraging the
141 creation of new public datasets through MPDA/TCIA and their dissemination in the field.

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