Quantitative Imaging Enters the Clinical Arena: A Personal Viewpoint

Robert J. Nordstrom

Cancer Imaging Program, National Cancer Institute, Bethesda, MD

Corresponding Author:
Robert J. Nordstrom, PhD
The Quantitative Imaging Network, Cancer Imaging Program of NCI,
9609 Medical Center Dr., Bethesda, MD 20892;
E-mail: nordstrr@mail.nih.gov

ABSTRACT

The National Cancer Institute's Quantitative Imaging Network (QIN) has thrived over the past 12 years with an emphasis on the development of image-based decision support software tools for improving measurements of imaging metrics. An overarching goal has been to develop advanced tools that could be translated into clinical trials to provide for improved prediction of response to therapeutic interventions. This article provides an overview of the successes in development and translation of new algorithms into the clinical workflow by the many research teams of the Quantitative Imaging Network.

INTRODUCTION

As Director of the National Cancer Institute's Quantitative Imaging Network (QIN) for the past 12 years, I have witnessed the growth of QIN from early development of decision support software tools that use imaging for measuring or predicting response to cancer therapies to the early entrance of tested and refined tools into clinical trials. This journey has shed light on the fact that translation into clinical workflow is every bit as challenging as the original steps of development and testing. Knowledge that the challenges associated with translating research from the laboratory to the clinical arena exist is not new, but it appears that this fact must be rediscovered every few years. Dr. Paul Ehrlich, 1908 Nobel Prize winner in medicine, stated, "The step from laboratory to patient's bedside...is extraordinarily arduous and fraught with danger." Although no details concerning the "danger" were provided by Dr. Ehrlich, his comment communicates the spirit of the difficulty experienced by QIN teams today.

OVERVIEW

QIN was initiated in 2008 with a program announcement and its first successfully reviewed application. Since that time, 43 teams have been supported to participate as members of the network, and 26 teams from around the world participated in the process of creating and testing clinical decision support tools for quantitative assessment of therapy response as associate members without National Cancer Institute (NCI) support. This growth in quantitative imaging is not isolated to QIN alone. Surveying PubMed, it is seen that there has been an increase in the number of articles containing the phrase "quantitative imaging" in the

title by over a factor of seven in the past decade (Figure 1). It should not be inferred that the network was a large motivating factor in this increased interest in quantitative imaging. Rather, the best we can say is that the network was created at an opportune time when interest in the challenges of quantitative imaging was maturing.

Over the past 12 years, applications to the network are traditionally received 3 times each year in response to an active program announcement published by the NCI. In each round, the applications are reviewed in a study section organized by NCI's Division of Extramural Activities. This process results in a network with staggered starts of its member teams with the expected effect of staggered degrees of progress toward eventual clinical testing of quantitative tools at any given time. With the large number of teams currently collaborating in the network, it is difficult to determine the performance readiness of each specific tool to enter clinical trials. Therefore, a method of benchmarking QIN tools was developed over a year ago (1). This process has enabled the network to prioritize the tools and to determine tools that are most prepared for entering clinical trials. To date, 67 tools have been benchmarked from a prebenchmark level (level 1) to clinical trial–ready (level 5).

BENCHMARKING OF TOOLS

This benchmarking process was highlighted in an earlier issue of *Tomography* (Volume 5, Number 1; 2019). However, this was not the first time that progress from QIN teams was highlighted in special issues of prominent journals. The first was in 2012 in *Magnetic Resonance Imaging* (Volume 30, Number 8). At this stage in the network, teams were focusing on the development of
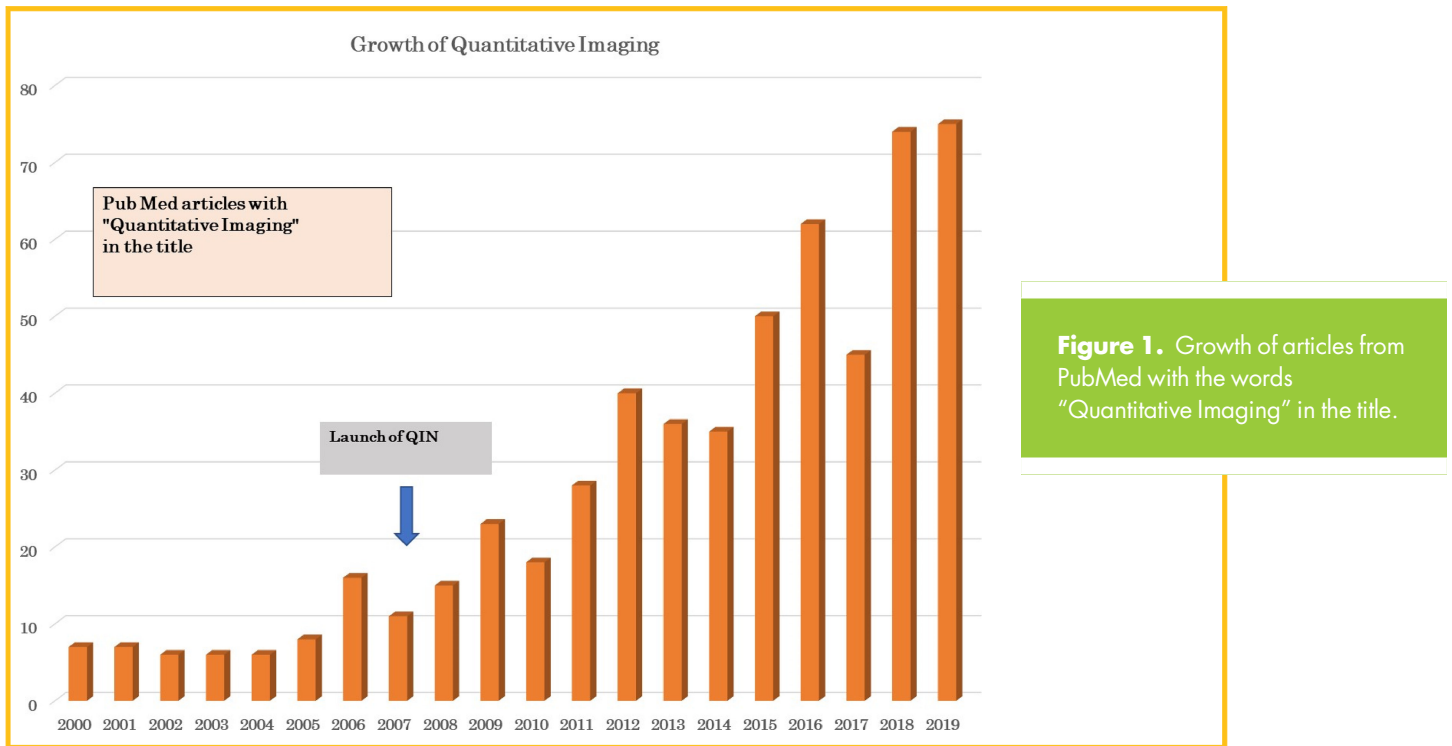
Figure 1. Growth of articles from PubMed with the words "Quantitative Imaging" in the title.

algorithms and methods for measuring or predicting response to therapies. The papers in that issue reflect this stage in quantitative imaging development.

In 2014, *Translational Oncology* (Volume 7, Number 1) published a collection of QIN research articles showing the status of network progress. At this point in the progression of the network, diversity in the advancement through the translation pathway can be seen. Papers emphasizing development still dominate, but a number of articles are seen that discuss advanced topics of reproducibility, multisite data collection, and clinical trial challenges. This diversity in translation maturity is the result of the staggered start dates for the teams in the network.

The 2016 issue of *Tomography* (Volume 2, Number 1) covered all aspects of quantitative imaging research from QIN at that point in the program. Topics from test–retest for radiomic stability to simulating the effects of spectroscopic magnetic resonance imaging for radiation planning in glioblastoma showed that the network was moving away from initial development of algorithms and methods to real-world testing and analysis of quantitative methods.

In the SPIE *Journal of Medical Imaging* (Volume 5, Number 1), QIN was invited to submit original research articles on quantitative imaging. By this time, the field had grown so large that a number of institutions outside those supported by the QIN program contributed to the special SPIE issue. Despite this, the articles from QIN show a sustained progress from development discussions to clinical evaluation of quantitative tools. In addition, a glance at the author lists shows extensive collaboration among QIN teams.

As mentioned earlier, *Tomography* (Volume 5, Number 1; 2019) highlighted the effort made by QIN to benchmark developed tools in order to prioritize tools and methods ready for clinical testing. This issue stands as a watershed between QIN as a

developer of quantitative imaging tools and QIN as a contributor of tools used in clinical evaluation. A complete list of the papers published in that issue of *Tomography* are listed in the References section of this paper [1–27].

Benchmark prioritization, however, is only the first step toward bringing qualified imaging tools into clinical utility. Announcing the availability and function of the clinically ready tools to appropriate users is another necessary task in the translation from development to clinical utility. To do this, QIN initiated efforts to present information on several clinically ready tools to the cooperative groups of the National Clinical Trial Network (NCTN). This process of presenting tools and their performance characteristics cannot be a one-time event, and the introduction of tools to these groups will continue. This issue of *Tomography* is an excellent example of another way to present QIN tools to the user community. Focusing specifically on tools and progress from the QIN, this issue shows the breadth of the challenges being met by the network.

QIN NETWORK OF EXPERTS AND ADVANCES

A strength of the network is the extent of collaboration that exists, as noted by the enclosed 24 articles coauthored by members of different teams within QIN (28–51). Another notable feature to highlight is the continued interest and use of deep learning and radiomics to extract quantitative information from medical images. QIN was an early subscriber and contributor to these methods, and several articles here show that the use of these information extraction methods in imaging is increasing.

QIN often tackles research challenges that individual research investigators ignore. I direct your attention to several important examples in this issue. The article, "Standardization in

Quantitative Imaging: A Multi-Center Comparison of Radiomic Features from Different Software Packages on Digital Reference Objects and Patient Data Sets" by McNitt-Gray et al. (35) shows not only the degree of collaboration that has been established in the network but also the type of challenge the investigators are choosing to attack. Standardization of software packages is a task that can be undertaken only when a large number of collaborating research groups come together and apply the necessary resources to accomplish the task.

Other studies that are necessary for acceptance of quantitative methods in the clinical environment include multisite uses of tools to determine performance characteristics in different clinical environments and imaging platforms. Smith et al. (29) look at this problem in "Multi-Site Technical and Clinical Performance Evaluation of Quantitative Imaging Biomarkers from 3D FDG PET Segmentations of Head and Neck Cancer Images."

Jones (28) provides insight into the workings of one of the several working groups of the network in her article, "Clinical trial design and development work group within the Quantitative Imaging Network." Other working groups in the network include bioinformatics/IT and data sharing, image analysis, and performance metrics, magnetic resonance imaging data collection, and positron emission tomography (PET)/computed tomography (CT) data collection.

QIN has had the privilege of receiving 2 research teams from Canada into the network. Both teams were supported by the Canadian Government and have been eager contributors to network progress even after their support ended. The group from Princess Margaret Hospital takes a serious look at 4DCT attenuation correction in gated PET for hypoxia (49). Researchers from the other Canadian member, the University of British Columbia, are part of the standardization article mentioned earlier (35).

Finally, I urge the readers to pay attention to the various articles on radiomics, deep learning, and data mining methods for extracting information from the images. These show that quantitative imaging is firmly rooted in the aforementioned statistical and analytical methods.

Direct support for QIN by NCI is now terminated, but that does not mean that research in quantitative imaging will not be supported in the future. Teams already part of the network will continue to be supported throughout their grant cycle, and new opportunities for quantitative imaging research can be provided through existing grant mechanisms such as the NCI parent announcement. Special funding to support the transition of tools into clinical utility is being planned and may be in place soon.

SUMMARY

Quantitative imaging has matured from small development and demonstration projects in isolated universities and clinics to a substantial evolutionary effort encompassing scientific and statistical skillsets. It is being used to show increased efficiency in clinical trials and to shedd light on important cancer characteristics. QIN has a strong history in moving quantitative imaging forward and will continue to do so for years to come.

REFERENCES

1. Farahani K, Tata D, Nordstrom RJ. QIN benchmarks for clinical translation of quantitative imaging tools. Tomography. 2019;5:1–6.
2. Yankeelov TE. The Quantitative Imaging Network: a decade of achievement. Tomography. 2019;5:A8–A8.
3. Chenevert TL, Malyarenko DI, Galban CJ, Gomez-Hassan DM, Sundgren PC, Tsien CI, Ross BD. Comparison of voxel-wise and histogram analyses of glioma ADC maps for prediction of early therapeutic change. Tomography. 2019;5:7–14.
4. Paudyal R, Konar AS, Obuchowski NA, Hatzoglou V, Chenevert TL, Malyarenko DI, Swanson SD, LoCastro E, Jambawalikar S, Liu MZ, Schwartz LH, Tuttle RM, Lee N, Shukla-Dave A. Repeatability of quantitative diffusion-weighted imaging metrics in phantoms, head-and-neck, and thyroid cancers: preliminary findings. Tomography. 2019;5:15–25.
5. Nunez DA, Lu Y, Paudyal R, Hatzoglou V, Moreira AL, Oh JH, Stambuk HE, Mazaheri Y, Gonen M, Ghossein RA, Shaha AR, Tuttle RM, Shukla-Dave A. Quantitative non-Gaussian intravoxel incoherent motion diffusion-weighted imaging metrics and surgical pathology for stratifying tumor aggressiveness in papillary thyroid carcinomas. Tomography. 2019;5:26–35.
6. Malyarenko DI, Swanson SD, Konar AS, LoCastro E, Paudyal R, Liu MZ, Jambawalikar SR, Schwartz LH, Shukla-Dave A, Chenevert TL. Multicenter repeatability study of a novel quantitative diffusion kurtosis imaging phantom. Tomography. 2019;5:36–43.
7. Virostko J, Sorace AG, Wu C, Ekrut D, Jarrett AM, Upadhyaya RM, Aver S, Patt D, Goodgame B, Yankeelov TE. Magnetization transfer MRI of breast cancer in the community setting: reproducibility and preliminary results in neoadjuvant therapy. Tomography. 2019;5:44–52.
8. Gurbani SS, Yoon Y, Weinberg BD, Salgado E, Press RH, Cordova JS, Ramesh KK, Liang Z, Vega JV, Voloschin A, Olson JJ, Schreibmann E, Shim H, Shu H-KG. Assessing treatment response of glioblastoma to an HDAC inhibitor using whole-brain spectroscopic MRI. Tomography. 2019;5:53–60.
9. Aryal MP, Lee C, Hawkins PG, Chapman C, Eisbruch A, Mierzwa M, Cao Y. Real-time quantitative assessment of accuracy and precision of blood volume derived from DCE-MRI in individual patients during a clinical trial. Tomography. 2019;5:61–67.
10. Parra NA, Lu H, Choi J, Gage K, Pow-Sang J, Gillies RJ, Balagurunathan Y. Habitats in DCE-MRI to predict clinically significant prostate cancers. Tomography. 2019;5:68–76.
11. Foltz W, Driscoll B, Lee SL, Nayak K, Nallapareddy N, Fatemi A, Menard C, Coolens C, Chung C. Phantom validation of DCE-MRI magnitude and phase-based vascular input function measurements. Tomography. 2019;5:77–89.
12. Machireddy A, Thibault G, Tudorica A, Afzal A, Mishal M, Kemmer K, Naik A, Troxell M, Goranson E, Oh K, Roy N, Jafarian N, Holtorf M, Huang W, Song X. Early prediction of breast cancer therapy response using multiresolution fractal analysis of DCE-MRI parametric maps. Tomography. 2019;5:90–98.
13. Huang W, Chen Y, Fedorov A, Li X, Jajamovich GH, Malyarenko DI, Aryal MP, LaViolette PS, Oborski MJ, O'Sullivan F, Abramson RG, Jafari-Khouzani K, Afzal A, Tudorica A, Moloney B, Gupta SN, Besa C, Kalpathy-Cramer J, Mountz JM, Laymon CM, Muzi M, Kinahan PE, Schmainda K, Cao Y, Chenevert TL, Taouli B, Yankeelov TE, Fennessy F, Li X. The impact of arterial input function determination variations on prostate dynamic contrast-enhanced magnetic resonance imaging pharmacokinetic modeling: a multicenter data analysis challenge. Tomography. 2019;5:99–109.
14. Bell LC, Semmineh N, An H, Eldeniz C, Wahl R, Schmainda KM, Prah MA, Erickson BJ, Korfiatis P, Wu C, Sorace AG, Yankeelov TE, Rutledge N, Chenevert TL, Malyarenko D, Liu Y, Brenner A, Hu LS, Zhou Y, Boxerman JL, Yen Y-F, Kalpathy-Cramer J, Beers AL, Muzi M, Madhuranthakam AJ, Pinho M, Johnson B, Quarles CC. Evaluating multisite rCBV consistency from DSC-MRI imaging protocols and postprocessing software across the NCI Quantitative Imaging Network sites using a digital reference object (DRO). Tomography. 2019;5:110–117.
15. Kim MM, Parmar HA, Aryal MP, Mayo CS, Balter JM, Lawrence TS, Cao Y. Developing a pipeline for multiparametric MRI-guided radiation therapy: initial results from a phase II clinical trial in newly diagnosed glioblastoma. Tomography. 2019;5:118–126.
16. McGarry SD, Bukowy JD, Iczkowski KA, Unteriner JG, Duvnjak P, Lowman AK, Jacobsohn K, Hohenwalter M, Griffin MO, Barrington AW, Foss HE, Keuter T, Hurrell SL, See WA, Nevalainen MT, Banerjee A, LaViolette PS. Gleason probability maps: a radiomics tool for mapping prostate cancer likelihood in MRI space. Tomography. 2019;5:127–134.
17. Stringfield O, Arrington JA, Johnston SK, Rognin NG, Peeri NC, Balagurunathan Y, Jackson PR, Clark-Swanson KR, Swanson KR, Egan KM, Gatenby RA, Raghunand N. Multiparameter MRI predictors of long-term survival in glioblastoma multiforme. Tomography. 2019;5:135–144.

18. Mattonen SA, Davidzon GA, Bakr S, Echegaray S, Leung ANC, Vasanawala M, Horng G, Napel S, Nair VS. 18F FDG positron emission tomography (PET) tumor and penumbra imaging features predict recurrence in non–small cell lung cancer. Tomography. 2019;5:145–153.

19. Byrd DW, Sunderland JJ, Lee T-C, Kinahan PE. Bias in PET images of solid phantoms due to CT-based attenuation correction. Tomography. 2019;5:154–160.

20. Ulrich EJ, Menda Y, Panto LLB, Anderson CM, Smith BJ, Sunderland JJ, Graham MM, Buatti JM, Beichel RR. FLT PET radiomics for response prediction to chemoradiation therapy in head and neck squamous cell cancer. Tomography. 2019;5:161–169.

21. Rubin DL, Akdogan MU, Altindag C, Alkim E. ePAD: an image annotation and analysis platform for quantitative imaging. Tomography. 2019;5:170–183.

22. Gurbani S, Weinberg B, Cooper L, Mellon E, Schreibmann E, Sheriff S, Maudsley A, Goryawala M, Shu H-K, Shim H. The Brain Imaging Collaboration Suite (BrICS): a cloud platform for integrating whole-brain spectroscopic MRI into the radiation therapy planning workflow. Tomography. 2019;5:184–191.

23. Paul R, Schabath M, Balagurunathan Y, Liu Y, Li Q, Gillies R, Hall LO, Goldgof DB. Explaining deep features using radiologist-defined semantic features and traditional quantitative features. Tomography. 2019;5:192–200.

24. Wu E, Hadjiiski LM, Stimala RK, Chan H-P, Cha KH, Richter C, Cohan RH, Caoili EM, Paramagul C, Alva A, Weizer AZ. Deep learning approach for assessment of bladder cancer treatment response. Tomography. 2019;5:201–208.

25. Svistoun I, Driscoll B, Coolens C. Accuracy and performance of functional parameter estimation using a novel numerical optimization approach for GPU-based kinetic compartmental modeling. Tomography. 2019;5:209–219.

26. Yang H, Guo X, Schwartz LH, Zhao B. A web-based response-assessment system for development and validation of imaging biomarkers in oncology. Tomography. 2019;5:220–225.

27. Lu L, Liang Y, Schwartz LH, Zhao B. Reliability of radiomic features across multiple abdominal CT image acquisition settings: a pilot study using ACR CT phantom. Tomography. 2019;5:226–231.

28. Jones EF, Buatti JM, Shu H-K, Wahl RL, Kurland BF, Linden HM, Mankoff DA, Rubin DL, Tata D, Nordstrom RJ, Hadjiyski L, Holdhoff M, Schwartz LH. Clinical trial design and development work group within the Quantitative Imaging Network. Tomography. 2020;6:60–64.

29. Smith BJ, Buatti JM, Bauer C, Ulrich EJ, Ahmadvand P, Budzevich MM, Gillies RJ, Goldgof D, Grkovski M, Hamarneh G, Kinahan PE, Muzi JP, Muzi M, Laymon CM, Mountz JM, Nehmeh S, Oborski MJ, Zhao B, Sunderland JJ, Beichel RR. Multi site technical and clinical performance evaluation of quantitative imaging biomarkers from 3D FDG PET segmentations of head and neck cancer images. Tomography. 2020;6:65–76.

30. Onishi N, Li W, Gibbs J, Wilmes LJ, Nguyen A, Jones EF, Arasu V, Kornak J, Joe BN, Esserman LJ, Newitt DC, Hylton NM. Impact of MRI protocol adherence on prediction of pathological complete response in the I-SPY 2 neoadjuvant breast cancer trial. Tomography. 2020;6:77–85.

31. Malyarenko DI, Newitt DC, Amouzandeh G, Wilmes LJ, Tan ET, Marinelli L, Devaraj A, Peeters JM, Giri S, Endt AV, Hylton NM, Partridge SC, Chenevert TL. Retrospective correction of ADC for gradient nonlinearity errors in multicenter breast DWI trials: ACRIN6698 multi-platform feasibility study. Tomography. 2020;6:86–92.

32. Ramesh K, Gurbani SS, Mellon EA, Huang V, Goryawala M, Barker PB, Kleinberg L, Shu H-KG, Shim H, Weinberg BD. The Longitudinal Imaging Tracker (BrICS-LIT): a cloud platform for monitoring treatment response in glioblastoma patients. Tomography. 2020;6:93–100.

33. Nguyen AA-T, Arasu VA, Strand F, Li W, Onishi N, Gibbs J, Jones EF, Joe BN, Esserman LJ, Newitt DC, Hylton NM. Comparison of segmentation methods in assessing background parenchymal enhancement as a biomarker for response to neoadjuvant therapy. Tomography. 2020;6:101–110.

34. Jaggi A, Mattonen SA, McNitt-Gray M, Napel SN. Stanford DRO Toolkit: digital reference objects for standardization of radiomic features. Tomography. 2020;6:111–117.

35. McNitt-Gray M, Napel S, Jaggi A, Mattonen SA, Hadjiiski L, Muzi M, Goldgof D, Balagurunathan Y, Pierce LA, Kinahan PE, Jones EF, Nguyen A, Virkud A, Chan HP, Emaminejad N, Wahi-Anwar M, Daly M, Abdalah M, Yang H, Lu L, Lv W, Rahmim A, Gastounioti A, Pati S, Bakas S, Kontos D, Zhao B, Kalpathy-Cramer J, Farahani K. Standardization in quantitative imaging: a multicenter comparison of radiomic features from different software packages on digital reference objects and patient data sets. Tomography. 2020;6:118–128.

36. LoCastro E, Paudyal R, Mazaheri Y, Hatzoglou V, Oh JH, Lu Y, Shridhar Konar A, Vom Eigen K, Ho A, Ewing JR, Lee N, Deasy JO, Shukla-Dave A. Computational modeling of interstitial fluid pressure and velocity in head and neck cancer based on dynamic contrast enhanced magnetic resonance imaging: feasibility analysis. Tomography. 2020;6:129–138.

37. Zhou L, Wang Y, Pinho MC, Pan E, Xi Y, Maldjian JA, Madhuranthakam AJ. Intra-session reliability of arterial spin-labeled MRI-measured non contrast perfusion in glioblastoma at 3T. Tomography. 2020;6:139–147.

38. Li K, Machireddy A, Tudorica A, Moloney B, Oh KY, Jafarian N, Partridge SC, Li X, Huang W. Discrimination of malignant and benign breast lesions using quantitative multi-parametric MRI: a preliminary study. Tomography. 2020;6:148–159.

39. Bobholz SA, Lowman AK, Barrington A, Brehler M, McGarry S, Cochran EJ, Connelly J, Mueller WM, Agarwal M, O'Neill D, Nencka AS, Banerjee A, LaViolette PS. Radiomic features of multi parametric MRI present stable associations with analogous histological features in patients with brain cancer. Tomography. 2020;6:160–169.

40. Whisenant JG, Williams JM, Kang H, Arlinghaus LR, Abramson RG, Abramson VG, Fakhoury K, Chakravarthy AB, Yankeelov TE. Quantitative comparison of prone and supine PERCIST measurements in breast cancer. Tomography. 2020;6:170–176.

41. Newitt DC, Amouzandeh G, Partridge SC, Marques HS, Herman BA, Ross BD, Hylton NM, Chenevert TL, Malyarenko DI. Repeatability and reproducibility of ADC histogram metrics from the ACRIN 6698 breast cancer therapy response trial. Tomography. 2020;6:177–185.

42. Yogananda CGB, Shah BR, Vejdani-Jahromi M, Nalawade SS, Murugesan GK, Yu FF, Pinho MC, Wagner BC, Emblem KE, Bjørnerud A, Fei B, Madhuranthakam AJ, Maldjian JA. A Fully automated deep learning network for brain tumor segmentation. Tomography. 2020;6:186–193.

43. Hadjiiski LM, Cha KH, Cohan RH, Chan H-P, Caoili EM, Davenport MS, Samala RK, Weizer AZ, Alva A, Kirova-Nedyalkova G, Shampain K, Meyer N, Barkmeier D, Woolen SA, Shankar PR, Francis IR, Palmbos PL. Intra observer variability in bladder cancer treatment response assessment with and without computerized decision support. Tomography. 2020;6:194–202.

44. Bell LC, Semmineh N, An H, Eldeniz C, Wahl R, Schmainda KM, Prah MA, Erickson BJ, Korfiatis P, Wu C, Sorace AG, Yankeelov TE, Rutledge N, Chenevert TL, Malyarenko D, Liu Y, Brenner A, Hu LS, Zhou Y, Boxerman JL, Yen Y-F, Kalpathy-Cramer J, Beers AL, Muzi M, Madhuranthakam AJ, Pinho M, Johnson B, Quarles CC. Evaluating the use of rCBV as a tumor grade and treatment response classifier across NCI Quantitative Imaging Network sites: part II of the DSC-MRI digital reference object (DRO) challenge. Tomography. 2020;6:203–208.

45. Cherezov D, Paul R, Fetisov N, Gillies RJ, Schabath MB, Goldgof DB, Hall LO. Lung nodule sizes are encoded when scaling CT image for CNN's. Tomography. 2020;6:209–215.

46. Li W, Newitt DC, Yun BL, Jones EF, Arasu V, Wilmes LJ, Gibbs J, Nguyen AA-T, Onishi N, Kornak J, Joe BN, Esserman LJ, Hylton NM. Tumor sphericity predicts response in neoadjuvant chemotherapy for invasive breast cancer. Tomography. 2020;6:216–222.

47. Lu L, Sun SH, Yang H, Linning E, Guo P, Schwartz LH, Zhao B. Radiomics prediction of EGFR status in lung cancer—our experience in using multiple feature extractors and the Cancer Imaging Archive data. Tomography. 2020;6:223–230.

48. Konar AS, Fung M, Paudyal R, Oh JH, Mazaheri Y, Hatzoglou V, Shukla-Dave A. Diffusion-weighted echo planar imaging using multiplexed sensitivity encoding and reverse polarity gradient in head and neck cancer: an initial study. Tomography. 2020;6:231–240.

49. Driscoll B, Vines D, Shek T, Publicover J, Yeung I, Breen S, Jaffray D. 4D-CT attenuation correction in respiratory-gated PET for hypoxia imaging: is it really beneficial? Tomography. 2020;6:241–249.

50. Paul R, Hassan MS, Moros EG, Gillies RJ, Hall LO, Goldgof DB. Deep feature stability analysis using CT images of a physical phantom across scanner manufacturers, cartridges, pixel sizes, and slice thickness. Tomography. 2020;6:250–260.

51. Do RKG, Reyngold M, Paudyal R, Oh JH, Konar AS, LoCastro E, Goodman KA, Shukla-Dave A. Diffusion-weighted and dynamic contrast-enhanced MRI derived imaging metrics for stereotactic body radiotherapy of pancreatic ductal adenocarcinoma: preliminary findings. Tomography. 2020;6:261–271.