For many years, radiologists have used limited subjective analysis of imaging findings to characterize lesions, and to predict and assess treatment results. The imaging armamentarium includes multiple modalities such as computed tomography (CT), magnetic resonance imaging (MRI), as well nuclear medicine studies. One commonly encountered example is the evaluation of MRI findings in the prostatic transition zone (TZ), notoriously difficult, given its typical heterogeneous signal intensities on T2-weighted MRI. Traditional evaluation of the TZ is associated with several limitations. It demands experience and it is also highly subjective. Moreover, there is a limit to what the human eye can perceive from images and find important details buried in the images.

In the words of Gillies et al, “images are more than picture, they are data.” Radiomics is the process of mining measurable variables that could be helpful for patients, in the same way that we dig for gems. When using radiomics, a computer analysis is applied to quantify the appearance of the pathology. It can either be direct, as in texture analysis, or more complicated, combining several measures, as in artificial intelligence. Compared to mining for gems, our work, however, is more difficult, as we do not know what constitutes a valuable finding.

There are several hurdles in our way:
1. What source(s) should be used? Studies usually employ MRI, CT, ultrasound, or positron emission tomography (PET)/CT. In the current article, Fasmer et al used MRI; while Yan et al also included clinical factors such as Ca125 and age. Fasmer et al used T1-weighted images (T1WI) after contrast in the arterial phase, while Yan et al combined several sequences, including diffusion-weighted imaged imaging, T2-weighted imaging, and T1WI.
2. For which conditions should we utilize radiomics? Most works are done on cancer and metastases and subclassified those into different mutation types, but also nonmalignant conditions.
3. What radiomics-derived metrics are relevant? There are currently hundreds to thousands of variables that advanced data processing can produce, but those variables are seldom named or recognized. However, some variables are more understandable and logical to the human mind. Skewness and homogeneity are such parameters. A slightly more complex, but still understandable variable, is kurtosis. Kurtosis is a normalized fourth moment of intensity distribution and heterogeneity. A flattened curve, nowadays a popular concept, has both lower peak and negative kurtosis, which means heavier tails. Kurtosis as a measure of heterogeneity has shown to be useful for prediction of tumor response. However, when applying too many variables to a dataset, without any theoretical explanation as to what theoretical physical correlation the parameter has, the risk of coincidental correlations is high, and might be difficult to reproduce.

Going back to our gem-analogy, our current status in radiomics is like choosing a spot with different rocks, not knowing which tool we should use, not knowing what we can find and how to find what we do not know, and not knowing if what we find has any value. This editorial should not act as a deterrent, but rather encourage us to the endless possibilities that lay ahead. There is mounting evidence, including the articles by Fasmer et al and Yan et al, to show that radiomics will be valuable for some selected scenarios.

Michael Torkzad, MD, PhD
Karolinska University Hospital Huddinge & European Telemedicine Clinic SL
Barcelona, Spain
* E-mail: michael.torkzad@gmail.com

References
1. Crivellaro C, Landoni C, Elisei F, et al. Combining positron emission tomography/computed tomography, radiomics, and sentinel lymph node mapping for nodal staging of endometrial cancer patients. Int J Gynecol Cancer 2020;30(3):378-382.
2. Gillies RJ, Kinahan PE, Hricak H. Radiomics: Images are more than pictures, they are data. Radiology 2016;278(2):563-577.
3. Fasmer K, Hodneland E, Dybvik JA, et al. Whole-volume tumor MRI radiomics for prognostic modeling in endometrial cancer. J Magn Reson Imaging 2021;53:928-937.
4. Yan BC, Li Y, Ma FH, et al. Preoperative assessment for high-risk endometrial cancer by developing and MRI- and clinical-based radiomics nomogram: A multicenter study. J Magn Reson Imaging 2020;52(6):1872-1882.

5. Thomas JV, Abou Elkassem AMA, Ganeshan B, Smith AD. MR imaging texture analysis in the abdomen and pelvis. Magn Reson Imaging Clin N Am 2020;28(3):447-456.

6. Boscolo-Berto R, Macchi V, Porzionato A, De Caro R. Editorial for “Preoperative assessment for high-risk endometrial cancer by developing an MRI- and clinical-based radiomics nomogram: A multicenter study.” J Magn Reson Imaging 2020;52(6):1883–1884.

7. Yan BC, Li Y, Ma FH, et al. Radiologists with MRI-based radiomics aids to predict pelvic lymph node metastasis in endometrial cancer: A multicenter study. Eur Radiol. 2020; Epub ahead of print. https://link.springer.com/article/10.1007/s00330-020-07099-8.

8. Robert B, Zlatescu M, Sijben A, et al. The use of magnetic resonance imaging to noninvasively detect genetic signatures in oligodendroglioma. Clin Cancer Res 2008;14(8):2357-2362.

9. Jakola AS, Zhang YH, Skjulsvik AJ. Quantitative texture analysis in the prediction of IDH status in low-grade gliomas. Neurol Neurosurg 2018;164:114-120.

10. Bowen SR, Yuh WTC, Hippie DS, et al. Tumor radiomic heterogeneity: Multiparametric functional imaging to characterize variability and predict response following cervical cancer radiation therapy. J Magn Reson Imaging 2018;47(5):1388-1396.

DOI: 10.1002/jmri.27460

Level of Evidence: 5
Technical Efficacy Stage: 3