WHAT IS RADIOMICS?

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1 INTRODUCTION

Radiomics is an emerging field that combines medical imaging techniques with data science to extract a vast array of quantitative features from images for clinical or research applications. These features, often imperceptible to the human eye, hold the potential to enhance healthcare and improve patient outcomes [1] through the identification of novel imaging markers that enable precise diagnosis, prognosis, and treatment planning for a variety of childhood diseases. Integration of radiomics with other data types, such as genomics [1], offers opportunities for further multi-modal insights, while longitudinal studies can establish radiomics' role in monitoring disease progression or treatment response.

Interpretability, accountability, and reliability are essential within a healthcare setting. In contrast to "black-box" AI approaches, radiomics typically integrate interpretable algorithms, ensuring that predictions and insights can be understood, validated, and trusted by clinicians, offering auditable workflows that are clear and reproducible.

While traditional radiological reporting is invaluable, it may not fully exploit all the complex information embedded within modern imaging data. Radiomics can provide additional value to conventional radiological reporting, enhancing our ability to characterise pathology quantitatively and equipping clinicians with meaningful insights to reliably inform decision making.

2 KEY CONCEPTS

Radiomics is the practice of transforming medical imaging into a set of well-defined quantitative features characterising a region of interest, such as pathology, providing insights through data-driven analysis (as well-detailed in [2]), following a workflow such as that shown in Figure 1. This process can be summarised as follows:

1) **Image Acquisition:** Modern medical imaging modalities, such as computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography, provide detailed anatomical and functional information to clinicians, and are commonly acquired clinically for diagnosis and treatment planning.
2) **Segmentation:** Quantitative analysis via radiomics requires the annotation of a Region of Interest (ROI), which delineates the boundary of the area in an image being investigated, serving as the volume from which radiomic features are extracted. Conventionally, ROIs were manually annotated, but are now increasingly annotated using semi-automated, or even fully-automated tools. Some investigations employ multiple ROIs, each highlighting different subregions of anatomy or disease that could exhibit distinct radiomic profiles.
3) **Feature Extraction:** Quantitative features are calculated from the segmented ROI(s), encompassing characteristics of pathology such as morphology, intensity, and texture. Each of these types of features exhibit varying levels of complexity and stability, with many capturing subtle imaging patterns, imperceptible to the human eye, which may correlate with underlying pathology.
4) **Data Analysis:** Advanced statistical methods and machine learning models analyse the extracted features. This stage identifies patterns, develops predictive models, and correlates imaging features with clinical outcomes or molecular data. Complementary sets of features can be extracted from multiple imaging modalities to further improve predictions.

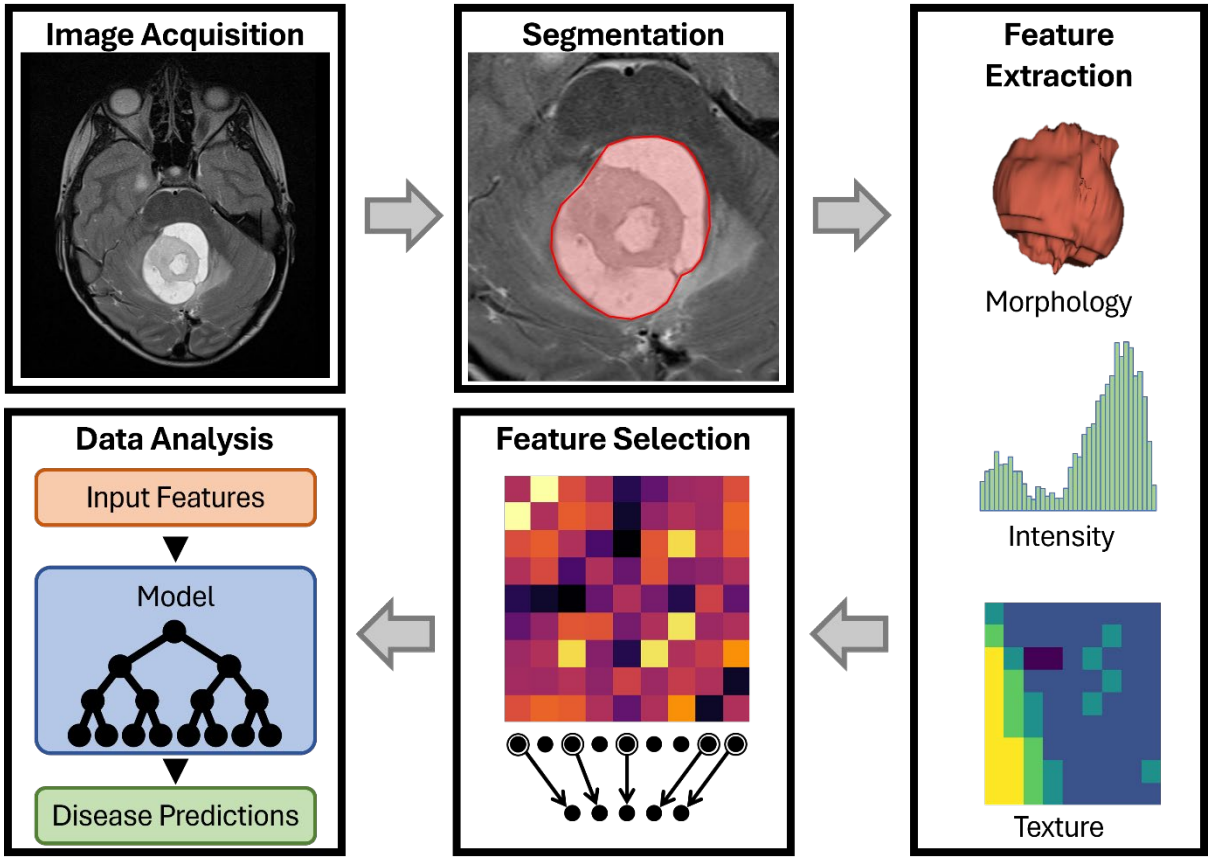

Figure 1: Steps required in a radiomic workflow, whereby images are first acquired and segmented, then different types of features are extracted, and finally passed to different algorithms or machine learning models for data analysis. An optional stage, feature selection, is included, typically used when extracting large numbers of features within relatively small cohorts. With the provided example image using a single region of interest, a diagnostic tool could pick up on the bright and cystic regions, rounded shape, and sharp tissue boundaries (via intensity, morphological and textural features respectively) to provide quick, quantitative identification of this brain tumour as a Pilocytic Astrocytoma.

3 Applications

Models utilising radiomic features have been applied across a wide range of paediatric disease cohorts to identify diagnostically and prognostically significant biomarkers with potential clinical applicability.

3.1 Acute Disease

Research into various acute paediatric conditions have employed radiomics to enhance diagnostic precision and support timely intervention. For example, using non-enhanced CT imaging only, radiomic analysis enabled the identification of early imaging biomarkers to distinguish necrotizing pneumonia in children [6], facilitating prompt and appropriate treatment decisions typically resulting in better patient outcomes.

3.2 Chronic Diseases

Radiomics offers a novel approach to quantifying disease progression in chronic conditions. Accurate radiomic models tracking subtle structural changes over time, could limit the need for supplementary sets of invasive tests, maintaining quality of care for patients whilst reducing patient impact and streamlining disease monitoring. For example, in cystic fibrosis (CF), where lung imaging is part of standard care, CT radiomic features alone have demonstrated good propensity to predict clinical markers of CF severity and exacerbation risk in adults [7].

3.3 Neonatal

In neonatology, radiomics has shown promise in prompt diagnosis of neonatal respiratory distress syndrome, utilising ultrasound imaging rather than typical radiological modalities [8]. Textural radiomic features combined with machine learning models enabled statistically significant improvements in diagnostic efficacy over junior physicians and with comparable performance to experts, demonstrating how radiomics can provide accurate diagnostic insights even when utilising non-standard imaging in small cohorts.

3.4 Neuro-oncology

Radiomics approaches have been shown to be able to classify different types of paediatric brain tumours using MRI acquired at diagnosis [3], and perform molecular subgrouping of medulloblastomas [4]. While these techniques are not yet a part of routine clinical decision-making, their potential to provide an early, non-invasive prediction of a tumour's molecular features could be valuable for informing initial patient and family counselling whilst awaiting definitive pathology results, or to assist neurosurgeons in deciding how aggressively to resect a tumour [9]. Radiomic feature analysis has also shown the ability to quantify and predict individual treatment responses [5], demonstrating the potential to radically improve patient outcomes through personalised care.

3.5 Neurodevelopmental Disorders

Medical imaging has demonstrated the potential to identify and characterise psychiatric or neurodevelopmental disorders using radiomics, such as attention-deficit/hyperactivity disorder (ADHD) [10, 11]. In these studies, radiomics demonstrated improved performance over clinical factors and volumetric measures, with the ability to also classify ADHD subtypes and treatment response. Following careful validation, these findings may complement current diagnostic practices, providing clinicians with objective metrics alongside self-reporting tools.

4 Challenges

Radiomics in paediatrics faces several challenges. Variability in imaging protocols and equipment, alongside imaging artefacts which are more common in children, such as motion artefact, can adversely impact feature reproducibility. Furthermore, vigilant monitoring of any imaging hardware and software improvement over time is critical to ensure any subtle changes in imaging parameters are not adversely impacting model accuracy. Image standardisation, harmonisation, and pre-processing is therefore an essential element of reproducible radiomic workflows, with continuous assessment required to identify and mitigate data drift.

Furthermore, paediatric disease cohorts tend to be smaller than adult counterparts, limiting data available for radiomic pipelines. [12] To ensure the statistical robustness and validity of findings, the large sets of radiomic features extracted from images require equally substantial numbers of patients in the cohort, making rigorous analytical techniques and collaborative, multi-centre studies essential to ensure robust, generalisable paediatric models.

The interpretation of radiomic data is further complicated within paediatrics, due to the influence of developmental changes on what is considered 'normal' at different ages. This variability underscores the importance of designing algorithms and identifying disease cohorts that account for age-specific variation, particularly given the relative scarcity of healthy control imaging in children compared to adults.

Manual annotation of pathology can also be time-consuming, and automated tools, often developed for adults, may not account for paediatric anatomical differences, requiring further research to develop robust automated segmentation solutions.

To become embedded in standard clinical practice, radiomics must produce explainable, auditable outputs that clinicians can interpret confidently. Furthermore, models need to be assessed to ensure the demonstrated

efficacy in research translates in a clinical environment when deployed alongside clinicians who are ultimately responsible for decision making. Biological validation of individual features is equally important, linking imaging findings to underlying pathology to enhance their credibility and relevance.

5 Conclusion

Radiomics offers a data-driven approach to paediatric imaging, transforming routine scans into a rich source of quantitative insights that complement traditional radiological practices. Its broad applicability across a range of conditions, from acute to chronic disease, cancer, and even neurodevelopmental disorders, highlights its potential to enhance diagnosis and improve prognostic accuracy.

Despite its promise, challenges such as imaging variability, segmentation limitations, and small cohort sizes persist. Advances in standardisation, robust feature selection, and explainable workflows are addressing these barriers, ensuring that radiomics outputs are interpretable and actionable in clinical settings. Validation through biological and clinical studies will continue to further strengthen its reliability and credibility.

With its wide applicability and focus on clinical translatability, radiomics is well-positioned to become a valuable tool in paediatric medicine, equipping clinicians with transparent, actionable insights to support decision-making, improving outcomes and advancing personalised healthcare for children.

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7 References

[1] M. A. Mazurowski, "Radiogenomics: What It Is and Why It Is Important," *Journal of the American College of Radiology,* vol. 12, no. 8, pp. 862-866, 2015.

[2] J. . E. van Timmeren, D. Cester, S. Tanadini-Lang, H. Alkadhi and B. Baessler, "Radiomics in medical imaging—"how-to" guide and critical reflection," *Insights into Imaging,* 2020.

[3] J. Novak and e. al., "Classification of paediatric brain tumours by diffusion weighted imaging and machine learning," *Scientific Reports,* vol. 11, no. 1, p. 2987, 2021.

[4] F.-C. Chang, T.-T. Wong, K.-S. Wu, C.-F. Lu, T.-W. Weng, M.-L. Liang, C.-C. Wu, W. Y. Guo, C.-Y. Chen and K. L.-C. Hsieh, "Magnetic resonance radiomics features and prognosticators in different molecular subtypes of pediatric Medulloblastoma," *PLOS ONE,* vol. 16, no. 7, 2021.

[5] R. Colen, C. Rolfo, M. Ak and e. al., "Radiomics analysis for predicting pembrolizumab response in patients with advanced rare cancers," *Journal for ImmunoTherapy of Cancer,* vol. 9, no. 4, 2021.

[6] X. Chen, W. Li, F. Wang, L. He and E. Liu, "Early recognition of necrotizing pneumonia in children based on non-contrast-enhanced computed tomography radiomics signatures," *Translational Pediatrics,* vol. 10, no. 6, pp. 1542-1551, 2021.

[7] G. Chassagnon, E. I. Zacharaki, S. Bommart, P.-R. Burgel, R. Chiron, S. Dangeard , N. Paragios , C. Martin and . M.-P. Revel, “Quantification of Cystic Fibrosis Lung Disease with Radiomics-based CT Scores,” *Radiology. Cardiothoracic imaging,* vol. 2, no. 6, 2020.

[8] W. Lin, . J. Ruan, Z. Liu, C. Liu, . J. Wang, . L. Chen, . W. Zhang and G. Lyu, “Exploring the diagnostic value of ultrasound radiomics for neonatal respiratory distress syndrome,” *BMC Pediatrics,* 2024.

[9] T. Mukherjee, O. Pournik and T. N. Arvanitis, “Magnetic resonance imaging (MRI) radiomics in paediatric neuro-oncology: A systematic review of clinical applications, feature interpretation, and biological insights in the characterisation and management of childhood brain tumours,” *DIGITAL HEALTH,* vol. 11, p. 20552076251336285, 2025.

[10] H. Sun, . Y. Chen, Q. Huang, S. Lui, X. Huang, . Y. Shi, X. Xu, . J. A. Sweeney and Q. Gong , “Psychoradiologic Utility of MR Imaging for Diagnosis of Attention Deficit Hyperactivity Disorder: A Radiomics Analysis,” *Radiology,* vol. 287, no. 2, pp. 620-630, 2018.

[11] M. Chen, Z. van der Pal, M. G. Poirot, A. Schrantee, M. Bottelier, S. J. Kooij, H. A. Marquering, L. Reneman and M. . W. Caan, “Prediction of methylphenidate treatment response for ADHD using conventional and radiomics T1 and DTI features: Secondary analysis of a randomized clinical trial,” *NeuroImage: Clinical,* vol. 45, 2025.

[12] M. Straus Takahashi, L. F. Donnelly and S. Siala, “Artificial intelligence: a primer for pediatric radiologists,” *Pediatric Radiology,* vol. 54, no. 13, pp. 2127-2142, 2024.