Crimson Publishers
Wings to the Research

Mini Review

Radiomics: From Images to Data - The Changing Nature of Clinical Evidence

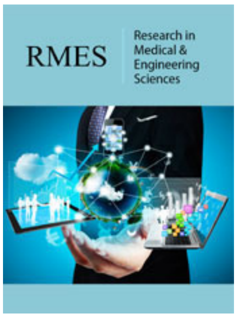
Suman Hazarika, MD, PhD[1,2]* and Nitish Hazarika MBBS[3]

[1]Chief radiologists, Apollo Hospitals Guwahati, Assam, India

[2]Prof of interdisciplinary studies, Girijananda Chaudhury University, Guwahati, Assam, India

[3]Radiology post graduate trainee, Assam Medical college, Dibrugarh, Assam, India

ISSN: 2576-8816



***Corresponding authors:** Suman Hazarika, Chief radiologists, Apollo Hospitals Guwahati, Assam, India

Submission: May 05, 2026

Published: June 23, 2026

Volume 12 - Issue 2

How to cite this article: Suman Hazarika, MD, PhD* and Nitish Hazarika MBBS. Radiomics: From Images to Data - The Changing Nature of Clinical Evidence. Res Med Eng Sci. 12(2). RMES.000785. 2026.
DOI: 10.31031/RMES.2026.12.000785

Abstract

For most of its history, radiology has been a visual discipline - one where diagnostic knowledge comes from imaging features that physicians learn, often painstakingly, to recognize through years of clinical exposure. Radiomics moves away from this in a fairly fundamental way, taking medical images and converting them into large quantitative datasets that can then be run through computational tools for analysis. Radiomics refers to the process of extracting a large number of quantitative features (measurable characteristics) from medical images and analyzing them using computers and statistical techniques. The idea is that instead of depending entirely on what a radiologist can see, you extract a broad range of imaging features (such as texture, shape, or intensity) and feed them into statistical or machine-learning models - and in doing so, surface patterns that wouldn't otherwise be visible. These patterns can, at least in many cases, point to underlying disease processes and have a genuine bearing on clinical decisions.

This article approaches radiomics not simply as another technical upgrade, but as something that arguably changes how radiological knowledge is generated in the first place. Computational methods (such as machine learning) bring with them a kind of diagnostic insight that sits outside the bounds of human perception, and that raises real questions about what the radiologist's role looks like going forward in a field that is becoming increasingly data-driven. None of this is without its difficulties, though. Reproducibility, meaning the ability to get similar results in different settings, is a persistent concern; results don't always transfer well across different patient populations. Making meaningful progress on these fronts will take more consistent methodological standards and validation that is genuinely rigorous - not just technically, but prospectively - before radiomics can realistically move into wider use.

Keywords: Radiomics; Artificial intelligence; Quantitative imaging; Precision medicine; Medical evidence; Diagnostic radiology

Introduction

Since Wilhelm Conrad Röntgen first described X-rays in 1895, radiology has been built, more or less, around what the human eye can see. Radiologists look at images, identify patterns - opacities, masses, anatomical distortions, asymmetries - and turn those observations into clinical diagnoses. Evidence, in this traditional framework, comes from what trained observers can perceive and make sense of.

The idea of structuring visual observation into a formal kind of knowledge was something Michel Foucault [1] explored in The Birth of the Clinic, where he described what he called the "medical gaze" - a disciplined way of seeing that gave clinical legitimacy to visual perception [1]. Radiology, arguably, is the most technologically elaborate expression of that tradition, using imaging to render the body's interior visible and interpretable.

More recently, computational methods have started to pull at this framework in significant ways. Radiomics - a growing area within quantitative imaging - works by extracting large numbers of mathematical features from medical images and analyzing them with statistical and machine-learning tools. Images, in this approach, stop being purely visual objects and become something closer to high-dimensional datasets. It's a shift that cuts deeper than technique alone - it puts pressure on older assumptions about where diagnostic knowledge comes from, and raises the uncomfortable possibility that clinically meaningful information might be sitting in patterns no radiologist would ever see.

Radiomics: Images become data

What radiomics actually does, stripped back, is pull quantitative features out of medical images - and a lot of them. These features cover a wide range of characteristics-signal intensity distributions, textural variation, geometric shape, spatial relationships within tissues-and using computational algorithms, hundreds of them can be derived from a single imaging study [2].

The idea was laid out clearly by Philippe Lambin [3] and colleagues, who made the case that medical images contain far more information than conventional visual inspection can access [3]. By systematically quantifying imaging characteristics, radiomics turns images into structured numerical datasets that can be linked to biological processes and clinical outcomes.

Gillies [4] and collaborators took this further, making the case that images shouldn't be thought of primarily as pictures at all - they are, in their view, mineable biomedical data [4]. Once you start extracting features and running statistical models on them, imaging stops being a purely descriptive exercise and starts producing quantitative biomarkers. The radiological image, in other words, becomes something you interrogate with a computer, not just something a physician looks at.

Invisible patterns and computational evidence

Perhaps the most striking thing about radiomics is its capacity to identify patterns that a human observer simply wouldn't catch. Quantitative features can pick up subtle variations in tissue heterogeneity, spatial complexity, and signal distribution that may reflect underlying biological states - things that don't always show up on any visual reading.

According to a landmark study by Aerts [5] and colleagues, radiomic features extracted from CT images can predict tumour phenotype and clinical outcomes across several cancer types [5]. This finding suggests that imaging datasets contain underlying biological information that becomes accessible through computational analysis.

Deep learning has added another dimension to this. Pairing handcrafted radiomic features with convolutional neural networks or transformer-based architectures produces hybrid models that draw on both engineered and learned representations - and in disease contexts like rectal cancer, hepatocellular carcinoma, and renal tumours, some of these have performed well enough to take seriously, particularly around treatment response, molecular markers, and recurrence risk [6,7].

But the problems don't disappear just because the methods have gotten more sophisticated. A radiomic signature that works at one institution often falls apart at another - scanner differences, protocol variations, segmentation inconsistencies all take their toll [8]. The patterns may be real. Whether they're reliable enough to act on is a separate question, and one the field hasn't fully answered.

What this amounts to, though, is a fairly different kind of evidence than radiology has traditionally worked with. Diagnosis used to rest on abnormalities a trained clinician could point to. Radiomics produces something else - statistical signatures built from large-scale quantitative analysis, where the meaning of a finding is established through modelling rather than perception. That's not a minor difference.

The changing nature of medical evidence

The rise of radiomics carries real implications for how medical imaging generates evidence. Historically, radiological knowledge has depended on interpretive skill-the radiologist's ability to synthesize visual findings with clinical context to reach a diagnosis. Evidence, in that model, is primarily qualitative and perception-based.

Radiomics offers a different model: one grounded in quantitative measurement and computational inference. Imaging features can be statistically associated with tumour genotype, treatment response, or prognosis, which means imaging can function as a source of quantitative biomarkers [4,9]. This fits naturally with the broader push toward precision medicine. Yet the real challenge in radiomics may not be feature extraction itself. The bigger problem begins after that. A radiomics model is built through multiple steps - image acquisition, reconstruction settings, lesion segmentation, feature extraction, feature selection, model building, and validation. Small variations at any of these stages can change the final result. Even lesion segmentation remains a practical problem. Two observers may outline the same tumour differently and generate different texture features. A model trained on retrospective datasets may perform very well within the same institution but fail when tested on different scanners, patient populations, or disease settings. Many published radiomics studies also work with relatively small datasets while extracting hundreds of features. This creates an obvious risk of overfitting, where the model learns patterns that do not hold up in real clinical practice. The central question, therefore, is not whether radiomics can detect hidden imaging patterns. It clearly can. The more important question is whether these patterns remain biologically meaningful and clinically reliable outside controlled research environments. This reflects a larger problem in modern medical AI. Producing more statistical signals is now relatively easy. Deciding which signals deserve clinical trust is much harder. Without prospective validation, reproducible workflows, and integration into real clinical decision-making, radiomics may produce many interesting associations that remain clinically fragile.

None of this is without its complications, though. Radiomic features shift with acquisition parameters and technical variability - reproducibility has been a headache for the field since the beginning. Results frequently don't travel well across populations or institutions. When deep learning enters the picture, interpretability becomes another sticking point, and clinicians are understandably reluctant to trust outputs they can't follow. Regulatory pressure around AI-based medical devices only adds to the friction [10].

Some of this is being tackled head-on. The Image Biomarker Standardization Initiative has been working to bring consistency to feature definitions, which should help with reproducibility over time [11]. There's also a noticeable shift in how research is being conducted - multicenter studies, more transparent reporting, and a greater emphasis on fitting radiomics into actual clinical workflows rather than just demonstrating it in controlled settings.

Recent literature, roughly 2023 to 2025, paints a mixed but arguably more honest picture of where things stand. When proper standardization and external validation are actually applied, radiomics models can hold up - especially in oncology, where treatment response prediction has seen some of the more convincing results. Yet systematic reviews from this same window make clear that very few proposed models ever make it into routine clinical use. The gap between what gets published and what gets used remains wide. If anything, that gap is the clearest sign that the field is finally reckoning with itself - less focused on what radiomics might do, more focused on what it can actually deliver.

Implications for the future radiologist

As quantitative imaging and AI become more embedded in clinical practice, the question of what this means for the radiologist becomes harder to sidestep. If computational tools can analyze imaging datasets with increasing sophistication, radiologists will need to engage more directly with quantitative methods and data science than they traditionally have.

AI models have already demonstrated an ability to identify imaging patterns linked to disease characteristics and outcomes [10]. In this environment, the radiologist may increasingly serve as someone who integrates visual interpretation, quantitative metrics, and algorithmic predictions - rather than relying on any one of these alone.

None of this necessarily means human expertise becomes less important. What seems more likely is that it changes in character. In oncologic imaging, for example, a radiologist using a radiomics-based tool might receive a prediction about tumour recurrence risk. The model can flag subtle features invisible to the human eye, but interpreting what that prediction actually means - how it fits with the patient's symptoms, prior history, and established imaging criteria - still requires clinical judgment. What that looks like in practice is still taking shape, but the direction seems clear enough. Reading images remains part of the job - but so does interrogating what an algorithm is actually telling you, weighing quantitative outputs against messy clinical realities, and deciding when to trust a model and when to question it. The radiologist, in this sense, becomes something closer to a translator: standing between the computational and the clinical, responsible for making sure the two actually connect.

Conclusion

Radiomics marks a genuine shift in how medical imaging produces knowledge. Converting radiological images into high-dimensional datasets makes accessible layers of information that lie beyond what human vision can reach. This moves the evidentiary basis of radiology away from perceptual interpretation and toward computational inference - a meaningful change, not just a technical one. As imaging science continues to develop, radiologists will increasingly work at the boundary between visual medicine and data science. Radiomics, in that sense, is less a destination than a transition - from image-based interpretation toward something that might be called data-driven imaging knowledge.

Author Contributions

Dr. Suman Hazarika: Conceptualization, primary idea, synthesis of arguments, drafting of manuscript.

Dr. Nitish Hazarika: Literature search, reference verification, and language polishing.

Conflict of Interest

The authors declare no conflict of interest.

AI Use Statement

Artificial intelligence tools (Chat GPT plus, Grammarly) were used to assist in language refinement, structural organization, and clarity of expression. All intellectual content, conceptual framing, and final approval of the manuscript were undertaken by the authors.

References

1. Foucault M (1963) The birth of the clinic: An archaeology of medical perception. Routledge, London.
2. Perniciano A, Loddo A, Ruberto CD, Pes B (2024) Insights into radiomics: impact of feature selection and classification. Multimed Tools Appl 84: 31695-31721.
3. Lambin P, Rios-Velazquez E, Leijenaar R, Carvalho S, van Stiphout RGPM, et al. (2012) Radiomics: Extracting more information from medical images using advanced feature analysis. Eur J Cancer 48(4): 441-446.
4. Gillies RJ, Kinahan PE, Hricak H (2016) Radiomics: Images are more than pictures, they are data. Radiology 278(2): 563-577.
5. Aerts HJWL, Velazquez ER, Leijenaar RTH, Parmar C, Grossmann P, et al. (2014) Decoding tumor phenotype by non-invasive imaging using a quantitative radiomics approach. Nat Commun 5: 4006.
6. Starmans MPA (2023) Radiomics: Data science in medical imaging and its clinical implications. Eur Radiol.
7. Park JE, Kim D (2024) Radiomics and deep learning in clinical oncology: Current status and future directions. Radiology.
8. Mali SA, Ibrahim A, Woodruff HC, Andrearczyk V, Muller H, et al. (2021) Making radiomics more reproducible across scanner and imaging protocol variations: A review of harmonization methods. J Pers Med 11(9): 842.
9. Kumar V, Gu Y, Basu S, Berglund A, Eschrich SA, et al. (2012) Radiomics: The process and the challenges. Magn Reson Imaging 30(9): 1234-1248.
10. Demircioğlu A (2025) Reproducibility and interpretability in radiomics: a critical assessment. Diagn Interv Radiol 31(4): 321-328.
11. Zwanenburg A, Vallières M, Abdalah MA, Aerts HJWL, Andrearczyk V, et al. (2020) The image biomarker standardization initiative. Radiology 295(2): 328-338.