AI-Driven Radiomics: Bridging Quantitative Imaging and Precision Medicine

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Abstract. Radiomics has transformed medical imaging by converting CT, MRI, PET, and ultrasound scans into quantitative features that capture tumor heterogeneity and inform clinical decision-making. While traditional handcrafted radiomics has shown promise in predicting survival and treatment response, it is limited by variability and lack of reproducibility. The integration of artificial intelligence, particularly deep learning, has expanded radiomics by enabling automated feature extraction, improved accuracy, and multimodal data fusion. Emerging approaches such as explainable AI and federated learning address interpretability and privacy challenges, supporting broader adoption. However, real-world translation requires harmonization of imaging protocols, validation in multi-center studies, and integration into clinical workflows. By combining quantitative imaging, computational modeling, and robust statistical methods, AI-driven radiomics has the potential to reshape precision oncology, offering more reliable tools for diagnosis, prognosis, and personalized therapy. Its future impact will depend on interdisciplinary collaboration and sustained investment to ensure reproducibility, transparency, and equity in clinical applications.

Keywords: Radiomics; Artificial Intelligence; Precision Medicine.

1. Introduction

Medical imaging is the cornerstone of modern medicine, offering clinicians detailed, non-invasive visualization of internal structures. CT, MRI, PET, and ultrasound scanning are routine in clinical and hospital settings, producing staggering levels of data every day [1]. Such images form the basis of diagnosis and disease monitoring, but these images also carry information beyond that which the naked eye is easily able to read. Deciphering such hidden information is one of the fundamental challenges in medical informatics.

This challenge was overcome through the creation of radiomics. Instead of just looking at scans in a descriptive fashion, radiomics converts them into collections of quantitative features that define shape, intensity, and texture [2]. Those features can be compared with genomic data, pathology, or clinical end points, and provide new insights on the biology of the disease. In cancer, scientists have applied radiomics for tumor segmentation, classification into subtypes, and even the definition of response to therapy. For some cancers, such as lung cancer and head-and-neck cancer, radiomic features have been predictive of survival and recurrence, sometimes even outclassing conventional clinical variables in terms of predictive capability.

But the method is limited: hand-engineered features can miss subtle biology, and outcomes often vary between scanners and from one institution to another. Those limitations have retarded clinical uptake and driven the community towards artificial intelligence (AI). Deep learning algorithms, particularly convolutional neural networks, can recognize intricate imaging patterns without human intervention and have widened the horizon of radiomics [3]. But AI comes with a price as well—it needs large, correctly annotated sets and often output that is difficult for human clinicians to interpret.

At this stage, statistical methods will play a central role. Techniques like penalized regression, dimension reduction, and Bayesian methods will be able to stop overfitting and enhance the model's robustness when dealing with small datasets [4]. No less valuable, statistical paradigms provide interpretability tools that can act as guides for clinicians into the rationale behind the output from a specific model. This aspect is vital when establishing credibility and further integrating radiomics into routine clinical practice.

More generally, these advances represent the aspirations of precision medicine. There is growing demand that healthcare professionals utilize tools that are adaptable to patient variability, that offer personalized recommendations on therapy, and that offer interpretability of rationale [5]. Radiomics, supported by artificial intelligence and statistical approaches, has the potential as one such tool. A combination of quantitative imaging, computational modeling, and interpretability seeks not only the enhancement of technical efficiency but the provision of consistent, individualized care in oncology. Such approaches offer quantitative precision, as well as interpretability enhancements, such that clinicians can comprehend and trust outputs from the model, a chief determinant that clinical success will be forthcoming.

Looking ahead, many challenges remain that are critical to the practical everyday use of radiomics. Data-sharing is often limited by data protection legislation, making the amassing of the large and diverse datasets needed by artificial intelligence programs difficult. Ethical considerations, especially those relating to fairness across different patient cohorts, also dominate. A model that works in one situation will not necessarily work in another, raising the specter of bias and inequality. Also, the practical everyday use of radiomics tools will require their easy incorporation into hospital workflows, without imposing any further demands on health professionals. Overcoming these challenges will be the final determinant as to whether radiomics will remain a research development or become a regular part of clinical decision-making.

Another is inter-institutional and interdisciplinary collaboration. Progress on radiomics is impossible without the collaboration between radiologists, oncologists, statisticians, and computer scientists. Multi-center trials are needed to test models on different populations and validate them in uncontrolled clinical environments. Also, technical issues like standardization of images, harmonization of data, and secure data exchange protocols must be resolved to develop reliable, generalizable systems. In addition, the process of the approval of regulators demands accuracy as well as transparency, and thus interpretability will remain the highest priority. Consequently, the next phase of the development of radiomics will be directed at the creation of bridges between technical development and clinical work, making sure that innovations turn into tools that can be trusted by clinicians and will be beneficial for the patients.

Ultimately, the trajectory of radiomics will be determined by further progress beyond initial proof-of-concept studies, toward definitive patient outcome improvement. Such a goal will be achievable through progress in methods, as well as through further investment in infrastructures, education, and transdisciplinary interaction. Should these factors be correctly aligned, then radiomics will have the potential to revolutionize oncologic practice by making precision medicine feasible, scalable, and clinically impactful.

2. Radiomics Basics

Radiomics has been a valuable tool in recent medical imaging, allowing conversion of routine scans into structured, quantitative data that can be used toward diagnosis, prognosis, and treatment planning. At the heart of the matter is the principle that medical images contain substantially more information than is possible to discern by the naked human eye. By extracting and analyzing thousands of features, radiomics creates a systematic system that correlates imaging patterns and biology, making this particularly valuable in the context of precision medicine [1, 4].

Most radiomics pipelines consist of four distinct stages: the acquisition of images, the delineating of the region of interest, the extracting of features, and the building of predictive models [3, 4]. In each, there are inherent challenges. For instance, images that have been derived from CT or MRI can be from varied scanners or gathered under varied parameters and hence may contribute unstable or inconsistent features. Efforts towards harmonization and standardization are, thus, paramount in the minimization of variability [3]. Another prominent stage is segmentation, which, despite still being expert-assisted/manual delineation-dominated, is frequently time-consuming as well as subjective. There, however, has been enhanced development towards AI-assisted segmentation approaches that have the goal of boosting speed as well as constancy, hence enabling larger-scale radiomics studies [1,2]. Feature extraction changes delineated areas into quantitative descriptors relating with shape, intensity, as well as texture. They then serve as inputs into predictive models with the goal of generating outcomes such as survival, recurrence, or response towards therapy [4].

The significant difference between these two types is one between handcrafted features and deep-learning-based methods. Handcrafted features are created by researchers who have CLINICAL REASONING in focus. They are interpretability-oriented and have been heavily utilized, e.g., when assessing tumor heterogeneity or when tracing changes along the course of therapy [4]. At the other extreme, deep learning methods have high-level representations directly from raw images as input and tend to have high predictive accuracy [1]. However, these methods have the demerit that large, annotated databases are required, and they possess the intrinsic 'black box' characteristic that forbids transparency. In a trade-off between accuracy and interpretability, hybrid methods that incorporate handcrafted features along with the output of deep learning have gained attention [2, 5].

Radiomics faces the common dilemma of the "high-dimensional, low-sample-size" problem. Thousands of features can be yielded from one session of imaging, yet the large number of studies generally involve no more than a few hundred patients. This imbalance increases the danger of overfitting, when the models show robust performance on the training sets but fail to transfer effectively to new data. In response, scientists apply statistical methods like penalized regression, dimensionality reduction, and cross-validation [2, 3]. More comprehensive collaborations across multiple institutions, as well as efforts such as federated learning, are on the horizon to increase sample sizes and build greater robustness [5].

Another challenge is the heterogeneity seen between different institutions and populations. A feature that is consistently reproduced in one medical center may not hold in another because the imaging protocols, patient populations, or clinical approaches differ [3]. In response, there are recommendations toward standardized definitions of features, harmonization methods, and multi-institutional benchmarking efforts. At the same time, broader societal considerations such as healthcare inequities act on the data sets used in radiomics. This scenario raises essential questions about the fair generalizability of the current models across varied clinical settings [4, 5].

Aside from technical issues, radiomics has also developed conceptually. Initial work was based on single-modality data, but contemporary work brings in multiple sources, such as genomics, pathology, and clinical biomarkers. Multimodality is motivated by the realization that imaging only presents a part of the process of the disease and that different data types, when combined, can offer a more complete description of the biology of the tumor. Another new direction is that of longitudinal radiomics, which follows imaging features longitudinally, attempting to capture how the tumor changes under therapy. Such uses could guide adaptive therapy, a major aim of precision oncology.

Clinical uptake is still lacking. While dozens of radiomics studies have looked promising, comparatively few tools are employed on a regular basis in hospital settings. This deficit is a reflection on issues of reproducibility and generalizability that have been raised by validation studies, demonstrating declines in performance beyond the initial research environment. Global initiatives, including the Image Biomarker Standardisation Initiative (IBSI), are attempting the same, with the goal of establishing clear definitions of features and test criteria. Analogously, multi-centre consortia and open data sets are assisting in the creation of benchmarks, as well as promoting transparency. Taken collectively, the projects represent a significant move towards making radiomics ready for regulatory approval, as well as ready for the real world.

Notwithstanding these obstacles, the field of radiomics is progressively broadening its horizons. Through enhanced standardization, extensive collaborative research initiatives, and the incorporation of statistical safeguards, the discipline is systematically advancing towards closing the divide between experimental investigations and routine clinical application.

3. AI Applications in Radiomics

The discipline of radiomics has seen tremendous growth over the past few years, spurred on by the growing volume of medical imaging data. The enormous number of CT, MRI, PET, and ultrasound images being produced on a daily basis across healthcare institutions is both a challenge and an opportunity. Classic radiomics, by means of segmentation and handcrafted feature extraction, built the initial foundation for the systematic quantification of imaging phenotypes. However, its limitations soon came into view: biases owing to operator variability, limited sets of features, and relatively low predictive capability. Artificial intelligence (AI) has started to revolutionize radiomics by allowing workflows that are automated, scalable, and often more accurate.

This section details three areas: (i) advancements in feature extraction and selection, (ii) clinical task-focused work, and (iii) new directions that push the boundaries of radiomics toward broader issues of precision medicine, ethics, and data control.

3.1. Feature Extraction and Selection

3.1.1. Convolutional Neural Networks (CNNs)

CNNs are the foundation of AI-based radiomics. By alternating layers of convolutional filters, pooling, and nonlinear activations, CNNs learn low-level to high-level features gradually. For instance, initial convolutional levels in a CT scan of lung tissue may recognize edges and textures, whereas deeper levels recognize shapes of the nodule or the abnormality in densities. This hierarchy is symbolic of the process radiologists use when reading the scan—beginning with large-scale patterns before localizing on details.

In oncology, CNN-based radiomics has achieved notable success. For lung cancer screening, CNNs trained on low-dose CT scans demonstrated higher sensitivity in identifying malignant nodules compared to handcrafted models [1]. Similar progress has been reported in breast cancer mammography, where CNN radiomics has improved early detection of ductal carcinoma in situ. In brain imaging, CNNs have been applied to glioma classification, distinguishing between high- and low-grade tumors with accuracy surpassing radiologists in some studies.

Despite their advantages, CNNs also introduce challenges. Training CNNs requires large datasets, but annotated medical images are limited. Moreover, CNN outputs can be difficult to interpret—why a model flags one lesion as malignant may not be obvious to clinicians. This “black box” nature contributes to skepticism in clinical settings [4].

3.1.2. Transformers and Attention Mechanisms

The introduction of transformer-based models has opened new avenues. Unlike CNNs, which primarily capture local spatial features, transformers use self-attention mechanisms to model long-range dependencies. This is particularly useful in radiomics, where tumor context within surrounding tissue can matter as much as the tumor itself. For instance, in predicting tumor invasiveness, information about peritumoral edema in MRI scans is as critical as the tumor margin. Transformers can weigh both regions simultaneously [2, 5].

Early research suggests that transformers improve performance in tasks such as liver lesion classification and multi-organ segmentation. Furthermore, attention maps can be visualized, which partially addresses interpretability concerns by showing which regions contributed most to a prediction. However, transformer models are even more data-hungry than CNNs, raising the same issues of dataset availability and computational cost.

3.1.3. AutoML and Transfer Learning

AI-driven radiomics does not always require starting from scratch. AutoML systems automate feature selection, model design, and hyperparameter tuning, allowing researchers with less technical expertise to build competitive models [3]. This democratizes access to AI, making it feasible for smaller institutions to participate in radiomics research.

Transfer learning, meanwhile, has become essential in dealing with small medical datasets. Pretrained models on large-scale image datasets (e.g., ImageNet) can be fine-tuned on medical imaging tasks with fewer samples. For example, a CNN pretrained on natural images can be adapted to classify prostate MRI scans, reducing the need for thousands of annotated examples. The downside is that natural image features may not perfectly transfer to medical imaging, so careful adaptation is necessary.

3.1.4. Hybrid Approaches

Hybrid models combine the strengths of both worlds: handcrafted features, which are interpretable and standardized, and deep features, which capture non-linear and abstract patterns. Studies in head and neck cancers have shown that hybrid radiomics models outperform either approach alone, offering both accuracy and transparency [6, 7].

3.2. Task-Specific Clinical Applications

Radiomics has been applied to nearly every stage of oncology care, from detection to treatment monitoring. Below are key application domains where AI-driven radiomics has already demonstrated clinical relevance.

3.2.1. Early Tumor Detection and Classification

Early diagnosis remains the most effective way to reduce cancer mortality. Radiomics models powered by CNNs have shown success in lung cancer screening programs, reducing false positives compared with manual interpretations [1]. In mammography, AI radiomics supports double-reading systems, offering a safety net for radiologists. In neuro-oncology, AI-enhanced MRI radiomics has distinguished glioblastoma from brain metastases, improving diagnostic precision.

These applications highlight radiomics as a “second reader,” augmenting rather than replacing clinical expertise. Nonetheless, issues of overfitting and generalizability persist, as models trained in one population may not transfer seamlessly to another. Personalized Radiotherapy and Drug Efficacy.

Radiomics can be used to guide therapy. Quantities extracted from scans taken before the start of therapy can be indicators of a tumor's likely response to radiotherapy, allowing dosing on a subject-by-subject basis [5]. Similar methods have been employed in the prediction of chemotherapy and immunotherapy response, allowing more personalized decisions on therapy [8, 9].

3.2.2. Prognosis and Recurrence Prediction

Prognostic modeling is another area where AI radiomics shines particularly brightly. PET-derived features have been found to be associated with progression-free survival in the scenario of head and neck cancers and have thus enabled the risk stratification of the patients [6]. AI-based radiomics signatures have also been linked with recurrence in breast cancer as well as survival in non-small cell lung cancer.

These models are not just academic exercises; they can shape clinical decisions. For instance, high-risk patients identified by radiomics models may receive intensified surveillance or adjuvant therapy. However, clinicians remain cautious about overreliance on models that may lack prospective validation.

3.2.3. Personalized Radiotherapy and Drug Efficacy

Radiomics has also been applied to optimize therapy. Pre-treatment CT features can predict tumor radiosensitivity, allowing oncologists to adjust radiation doses to individual patients [5]. Radiomics models have predicted immunotherapy response in melanoma and non-small cell lung cancer, guiding patient selection for costly and potentially toxic treatments [4, 9].

Drug development also benefits: AI radiomics can serve as an imaging biomarker in clinical trials, identifying early response or resistance patterns before clinical symptoms emerge. This accelerates the evaluation of novel therapies.

3.2.4. Multi-Cancer and Non-Cancer Applications

While oncology dominates radiomics research, AI-driven radiomics is expanding into cardiovascular, neurological, and inflammatory diseases. For example, radiomics applied to cardiac MRI can detect subtle changes in myocardial tissue, offering early warning for heart failure. In neurology, AI-enhanced MRI radiomics has supported diagnosis of Alzheimer’s disease by highlighting microstructural changes invisible to conventional analysis. These examples underscore the broad potential of radiomics beyond cancer.

3.3. Emerging Directions

3.3.1. Multi-Modal Data Fusion

Radiomics is rarely sufficient in isolation. Combining imaging features with genomic, proteomic, and clinical data can provide a richer, systems-level understanding of disease [6, 7]. For example, radiogenomic models have linked CT radiomics features to EGFR mutations in lung cancer, enabling non-invasive biomarker prediction. Clinical variables such as patient age, smoking history, and performance status further improve model reliability.

Multi-modal fusion, however, requires careful handling of heterogeneous data sources and raises challenges in standardization and computational complexity. Multi-Modal Data Fusion. One clear trend is combining radiomics with other types of data, such as genomics, proteomics, or clinical records. This “multi-modal” integration connects imaging phenotypes to biological mechanisms, which may lead to more reliable models for precision oncology [6, 7].

3.3.2. Explainable AI (XAI)

Interpretability is a recurring theme in radiomics. While CNNs and transformers achieve high accuracy, their “black box” nature undermines clinical trust. XAI methods address this gap by visualizing which features, or image regions drive predictions [4, 10]. For example, heatmaps overlaid on CT scans can indicate the regions influencing a malignancy prediction. XAI also aligns with ethical and legal requirements: regulatory agencies increasingly demand that AI models be explainable for clinical approval.

3.3.3. Federated Learning and Data Privacy

Medical images are protected by strict privacy laws, limiting data sharing across hospitals. Federated learning provides a solution: models are trained locally at each institution, and only parameter updates—not patient data—are shared. Studies show federated radiomics models perform nearly as well as pooled-data models, with the added benefit of privacy preservation [2, 9]. This approach also helps to address bias by incorporating data from diverse populations without requiring centralized storage.

3.3.4. Ethical, Regulatory, and Practical Considerations

AI-driven radiomics raises ethical and regulatory questions. Who is responsible if an AI model misclassifies a tumor? How can we ensure fairness across populations with different socioeconomic or genetic backgrounds? These questions highlight the need for not just technical innovation but also policy development [8]. Regulators like the FDA and EMA are beginning to develop frameworks for AI in medical imaging. Clinical trials now include AI-based radiomics biomarkers, but widespread approval will depend on multi-center validation and post-market surveillance.

To summarize, AI applications in radiomics span from early detection to treatment optimization, and from single-modality imaging to multi-modal data fusion. While technical advances are impressive, clinical adoption depends on addressing interpretability, reproducibility, and ethical concerns. Radiomics sits at the intersection of technology and medicine, requiring collaboration between computer scientists, clinicians, statisticians, and policymakers.

4. Summary

Radiomics has become a key part of precision medicine, and when combined with artificial intelligence, has increased both the technical efficiency and clinical usability of the former. By breaking through the limitations imposed on handcrafted descriptors, artificial intelligence has allowed the radiomics models to detect complex features, increase accuracy, and facilitate clinical decision-making in areas like early diagnosis, prognosis, and personalized therapy. Such advances represent the capability of artificial intelligence in boosting the ordinary statistical approaches and helping radiomics reach practical usability in the clinical domain. However, several challenges need to be overcome before radiomics can be reliably integrated into clinical work. Datasets remain heterogeneous and often have insufficient size to accommodate complex models. Data obtained in one medical institution does not always show reproducibility in another, and the black-box nature of deep learning erodes clinical confidence. Ongoing work on multi-modal fusion, explainable AI, and federated learning hold out hope; however, further validation studies on multiple institutions remain the need of the hour.

Radiomics, enhanced by artificial intelligence, represents one of the most promising tools in precision medicine. Its value lies not only in extracting quantitative features from images but also in integrating them with other sources of clinical knowledge. CNNs and transformers have pushed radiomics beyond traditional handcrafted features, enabling earlier tumor detection and more accurate prognosis. Applications now span multiple domains, including radiotherapy planning, immunotherapy response prediction, and even non-oncological diseases.

At the same time, limitations remain. Radiomics studies often rely on relatively small, institution-specific datasets, which hinders reproducibility. Data harmonization efforts such as the Image Biomarker Standardisation Initiative are addressing variability, but more work is needed. Another barrier is interpretability: physicians are hesitant to trust black-box predictions without clear rationale. Explainable AI techniques are a step in the right direction, but their utility in real-time clinical decision-making is still being tested.

Privacy concerns also shape the future of radiomics. Federated learning has shown that it is possible to train models across institutions without sharing sensitive patient data [2,9]. This is especially important for building diverse datasets that reflect real-world populations, rather than models biased toward a single demographic group. Looking forward, several priorities emerge. First, multi-modal fusion—combining radiomics with genomics, proteomics, and clinical records—offers the potential for holistic, individualized care. Second, clinical validation in prospective, multi-center trials is essential for gaining regulatory approval. Third, ethical frameworks must guide AI radiomics so that it promotes equity and avoids reinforcing existing disparities.

In conclusion, AI-driven radiomics has already demonstrated clear value in precision medicine, but its broader adoption will depend on solving challenges of interpretability, reproducibility, and privacy. With interdisciplinary collaboration and careful attention to clinical realities, radiomics can move from research to routine practice, offering tangible benefits for cancer patients and beyond.

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