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Review

Radiomics in oncology: A mini-review of principles, applications and challenges

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Abstract: Radiomics, a quantitative approach to medical imaging, employs computational methods to extract features from the images, revealing hidden characteristics of specific regions. This emerging field leverages advanced techniques to analyze a spectrum of features from modalities, including computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET) scans, aiming to decode tissue characteristics, disease progression, and treatment responses. The radiomics workflow integrates image acquisition, segmentation, feature selection, and data integration, utilizing advanced techniques such as deep learning, machine learning, and data mining. Radiomics demonstrates considerable potential in cancer detection and management, exhibiting high sensitivity and specificity in distinguishing between benign and malignant tumors and predicting outcomes. However, challenges such as imaging protocol variability, overfitting, and standardization requirements impede its broad clinical adoption. Innovations in multi-modal radiomics, deep learning, and genomics integration strive to mitigate these constraints. This review elucidates radiomics' capabilities, current applications, benefits, challenges, and future directions in oncology.

Keywords: radiomics; artificial intelligence; machine learning; cancer detection; medical imaging

1. Introduction to radiomics

Radiomics originates from 'radio-' (radiation or radiology) and '-omics,' a suffix denoting comprehensive study in various fields like genomics, proteomics, and metabolomics [1]. Consequently, radiomics focuses on extracting numerous features from radiological images to find hidden features of specific regions. These features include shape, texture, and intensity patterns, which are not readily visible to the human eye [2]. By utilizing computational techniques, radiomics aims to transform standard medical images, such as computed tomography (CT) scans, magnetic resonance imaging (MRI), and positron emission tomography (PET) scans, into high-dimensional data that can be analyzed to extract valuable information about tissue characteristics, disease progression, and treatment response [3,4].

2. Principles of radiomics

The workflow of radiomics is a series of consecutive but interconnected steps: (a) acquiring medical images; (b) identifying and segmenting regions of interest (ROI) or volumes of interest (VOI); (c) extraction of descriptive texture features from the ROIs or VOIs; (d) statistical selection of the parameters closely associated

with the clinical condition under study; and (e) data integration, standardization, classification, and mining processes [5].

2.1. Image acquisition and segmentation

Medical imaging is essential in modern healthcare, offering crucial data for disease diagnosis, monitoring, and treatment evaluation. Each imaging modality presents distinct advantages and challenges, providing varying anatomical and physiological information influenced by acquisition protocols, artifacts, and noise. Choosing the appropriate imaging modality or a combination is vital in radiomics, aligning with the study's objectives and the distinct characteristics of the targeted organ or tumor [6]. In the radiomics workflow, preprocessing often precedes contouring and segmentation, aiming to enhance image quality through advanced reconstruction techniques applied to raw data. Segmentation is a critical step where ROIs or VOIs are identified and delineated. Traditional manual contouring, typically performed by specialists, has been conventional. However, it may introduce variability and bias. While manual methods may suffice for smaller cohorts with experienced professionals, they become impractical for larger datasets due to cost and time constraints. Semi-automatic or automatic segmentation techniques enhance consistency and efficiency, thereby reducing variability and bias. This makes them particularly suitable for extensive studies [7].

2.2. Feature extraction and selection

In this stage, a large number of quantitative features are extracted from medical images. These features can be categorized into different types, such as first-order statistics (e.g., mean, variance), second-order statistics (e.g., texture features), and higher-order statistics (e.g., fractal dimensions). These features capture various aspects of the underlying tissue properties and can provide insights into the tissue microenvironment and disease state [2,8]. With the abundance of extracted features, selecting the most relevant and informative ones for further analysis is crucial. Feature selection techniques, such as correlation analysis, mutual information, and recursive feature elimination, are employed to identify the most discriminative features that distinguish between tissue types or disease conditions [5,9].

2.3. Data integration, classification, and the data mining process

In radiomics, once the most representative parameters of the studied object, like a tumor, are identified, the data are processed through integration, classification, and mining. Computational techniques, emulating human decision-making, have become pivotal across various research fields, particularly in medical imaging. Advanced algorithms, encompassing decision trees, deep learning, machine learning, and data mining, are increasingly employed to automate the classification of imaged tissues as healthy or abnormal. These techniques enhance the precision and efficiency of radiomics analysis, serving a wide range of research and clinical applications [10,11].

3. Current applications of radiomics in cancer detection and management

Addressing the complexities of intricate tumors requires a multifaceted approach, given the challenges in both diagnosis and treatment [12,13]. Radiomics has shown considerable promise in navigating these complexities. For instance, in a meta-analysis involving 8773 patients, MRI-based radiomics models exhibited a high sensitivity of 0.91 (95% CI: 0.89–0.92) and specificity of 0.84 (95% CI: 0.82–0.86) in distinguishing between benign and malignant breast lesions [14]. Furthermore, a meta-analysis focusing on lymph node metastasis (LNM) detection in colorectal cancer highlighted the efficacy of radiomics in guiding surgical interventions. The analysis yielded a pooled area under the curve (AUC) of 0.814 (95% CI: 0.78–0.85), with sensitivity and specificity values of 0.77 (95% CI: 0.69–0.84) and 0.73 (95% CI: 0.67–0.78), respectively. Remarkably, these radiomics models significantly outperformed radiologists ($p < 0.001$), emphasizing their potential as valuable tools in clinical decision-making and patient care [15]. Additionally, Radiomics features have been utilized to characterize tumors based on their molecular and histological properties. This enables the identification of distinct tumor subtypes, which can have implications for treatment planning and personalized medicine [16].

Radiomics-based biomarkers play a crucial role in monitoring treatment response and evaluating tumor progression or regression across challenging malignancies like lung cancer, glioma, and breast cancer, particularly in the context of immunotherapy [17,18]. These biomarkers provide quantitative metrics that complement conventional imaging assessments and can serve as early indicators of treatment efficacy or resistance. Furthermore, radiomics analysis aids in predicting patient outcomes such as survival and recurrence. In a prospective study focusing on locally advanced breast cancer (LABC), pre-treatment quantitative ultrasound (QUS)-radiomics identified a higher risk of disease recurrence before initiating treatment. These predictive models help clinicians strategize patients according to risk profiles, enabling tailored treatment strategies for improved clinical outcomes [19].

4. Advantages and challenges of radiomics in cancer detection

Radiomics offers several advantages over traditional imaging analysis methods in cancer detection. It leverages existing medical images, eliminating the need for invasive procedures or additional imaging scans. This reduces patient discomfort, risk of complications, and healthcare costs associated with repeated imaging examinations. Furthermore, by capturing detailed information about tumor heterogeneity and the microenvironment, radiomics significantly enhances personalized medicine approaches [20]. This capability allows clinicians to tailor treatment plans based on individual patient characteristics, leading to more effective and targeted therapies. Radiomics provides a framework for analyzing medical images, enabling objective and reproducible assessment of tumor characteristics and treatment response. Consequently, this improves the consistency and reliability of

diagnostic and prognostic evaluations across various healthcare settings [21]. The radiomics approach has recently emerged as a non-invasive diagnostic tool, providing clinicians with a new perspective on disease management, particularly in surgical oncology. Consequently, there has been a surge in research papers exploring the applicability of radiomics in different cancers [15]. To visualize the current trend of radiomics applications across various malignancies, we created a bibliometric network map with the help of the PubMed database searching radiomics and neoplasms medical subject headings and VOSviewer software **Figure 1**.

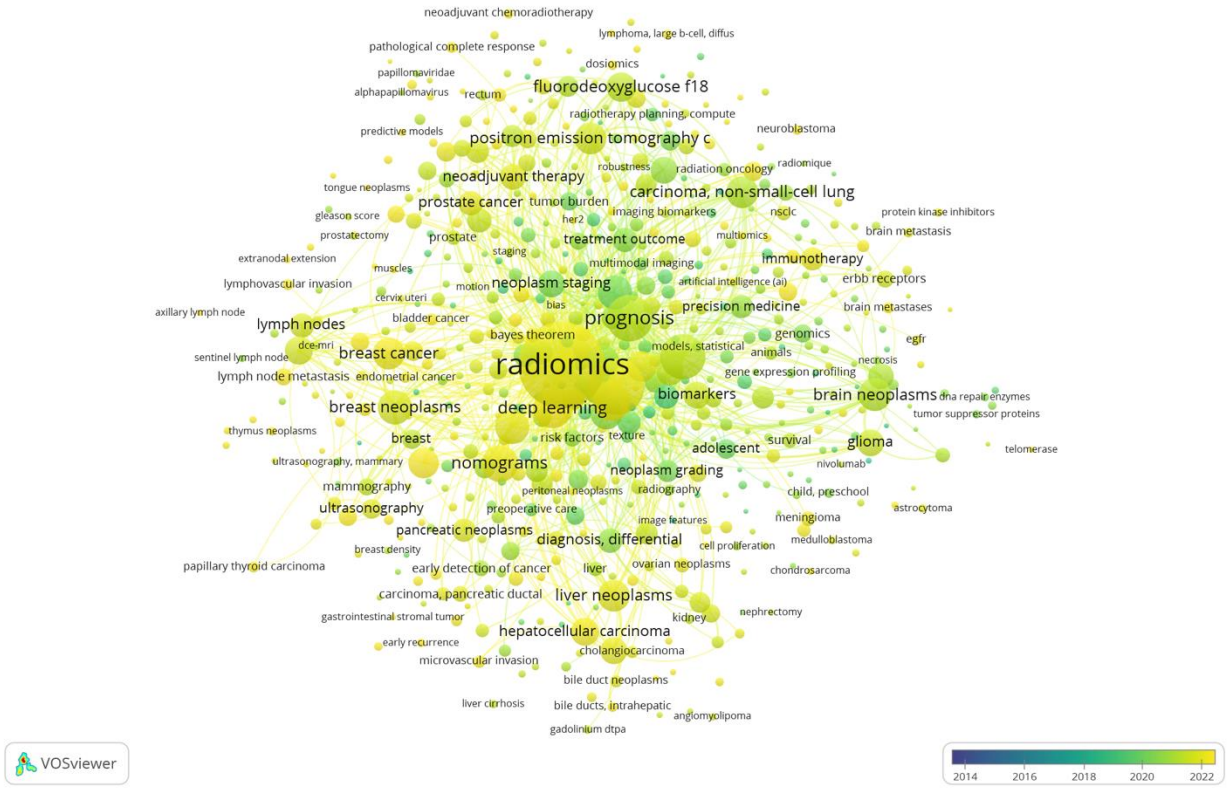

Figure 1. The bibliometrics network map illustrates the evolution and interconnections of radiomics-related studies in malignancies over the past decade, using bubble size to indicate publication frequency and color to represent a chronological progression based on the PubMed database.

Despite its potential, radiomics faces several challenges and limitations that must be addressed for widespread clinical adoption. Notably, variability in imaging protocols, equipment, and acquisition parameters can influence radiomics features and compromise their reproducibility and generalizability [22,23]. Moreover, standardization of imaging protocols and feature extraction methods is essential to ensure consistency and reliability of radiomics analyses across different institutions and platforms. Overfitting is a common issue in radiomics modeling, where the predictive model performs well on the training data but fails to generalize to new, unseen data. Robust feature selection, regularization techniques, and validation strategies are required to mitigate overfitting and improve the generalizability of radiomics models [15,22]. Recent advances in radiomics have focused on addressing its limitations and harnessing its full potential through innovative approaches and technologies such as multi-modal radiomics, deep learning approaches, and

integration with genomics and proteomics [24,25]. However, the suboptimal quality in reporting current radiomics studies, as assessed based on the RQS by studies, suggests a generally low standard, with an overall average score of approximately 50% [15]. These findings indicate that the results from current studies may lack reproducibility, limiting the widespread implementation of radiomics in clinical applications. Moreover, radiomics studies in the future require large-scale multicenter studies; prospective validation and integration into clinical practice guidelines are needed to demonstrate the clinical utility, cost-effectiveness, and impact on patient outcomes.

5. Conclusion

In the dynamic landscape of oncology, radiomics emerges as a transformative approach, integrating advanced computational techniques with multi-modal imaging data to reshape cancer detection and management. While radiomics offers remarkable opportunities for personalized medicine and early detection, it faces inherent challenges. Continued research, large-scale studies, and integration into clinical guidelines are imperative to validate radiomics' clinical utility, enhance reproducibility, and realize its impact on improving patient outcomes in oncology.

Conflict of interest: The authors declare no conflict of interest.

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