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The Role of Radiomics in Precision Oncology: A Comprehensive Review

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ABSTRACT:

Background: Cancer, a genetic disorder caused by uncontrolled cell proliferation, is a leading cause of death globally. Advances in precision oncology aim to tailor treatments based on individual tumor characteristics, enhancing treatment efficacy and minimizing side effects. Radiomics, the extraction of quantitative data from medical imaging, has emerged as a valuable tool in cancer diagnosis, treatment planning, and monitoring. The integration of radiomics with artificial intelligence (AI) promises to further personalize cancer treatment strategies.

Aim: This review aims to explore the role of radiomics in precision oncology, highlighting its applications, methodologies, and potential to improve cancer management.

Methods: The review examines the role of various imaging techniques in oncology, including traditional methods like X-rays and advanced technologies such as MRI, CT, PET/CT, and MRI. It discusses how radiomics builds on these techniques to extract quantifiable features for predictive modeling, emphasizing the potential of AI and big data in analyzing these features. The review also addresses the integration of AI in radiomics for enhancing cancer treatment decisions.

Results: Radiomics provides a more comprehensive analysis than traditional imaging by extracting multiple quantitative features, such as shape, texture, and intensity. AI-driven models using these features can predict treatment outcomes, assess tumor response, and identify potential recurrence. The review discusses AI techniques, including machine learning (ML) and deep learning (DL), and their applications in improving cancer treatment precision.

Conclusion: The integration of radiomics with AI in precision oncology holds significant promise for improving cancer diagnosis, treatment, and monitoring. However, challenges such as variability in imaging protocols and reproducibility need to be addressed for radiomics to be more widely applicable in clinical settings.

KEYWORDS: Radiomics, Precision Oncology, Imaging, Artificial Intelligence, Cancer Treatment, Machine Learning, Deep Learning, Imaging Biomarkers, Tumor Response.

Introduction:

Cancer is a pathological disorder that occurs when biological processes, such as cell signaling, are disturbed, leading to uncontrolled cell proliferation [1–4]. Malignant cells have the capacity to metastasize to far organs, infiltrate neighboring tissues, or do both actions. Cancer is categorized as a genetic condition due to abnormalities in genes that govern essential biological functions, especially cell division and differentiation. These genetic modifications disrupt normal cellular functions, resulting in uncontrolled proliferation and tumorigenesis. Typically, the body can recognize and eradicate these genetically modified cells before they advance to malignancy [1–4]. As humans age, the body's capacity to eliminate these changed cells declines, thereby heightening the chance of cancer development in later life. Every cancer kind is distinctive, propelled by specific genetic alterations. There are about 100 forms of cancer, which can be classified into categories including carcinomas, sarcomas, lymphomas, myelomas, leukemia, brain and spinal cord tumors, germ cell tumors, neuroendocrine tumors, and carcinoid tumors [1–4]. According to Globocan 2018, roughly 18.1 million new cancer cases are diagnosed globally each year. In 2020, projections indicated 10.3 million cancer-related fatalities and 19.3 million new cases worldwide. Significantly, there has been a rise of 1.2 million cancer diagnoses in the past two years alone [6]. Among the 19.3 million new cases, around 9.5 million (49.2%) are documented in Asia, succeeded by Europe (22%), the Americas (13.3%), Latin America and the Caribbean (7.6%), and Africa (5%). The three most prevalent malignancies worldwide are breast cancer (11.7%), lung cancer (11.1%), and colorectal cancer (10.1%). The Globocan 2020 report indicates that breast cancer is the most prevalent among women at 24.5%, but lung cancer (14.3%) and prostate cancer (14.1%) are the most common among men globally. This article aims to examine the amalgamation of radiomics and artificial intelligence (AI) within precision oncology.

Role of Imaging in Cancer Treatment:

The treatment of cancer is a complex and protracted process that is frequently not simple. The treatment process commences with the disease diagnosis, which may, in certain instances, persist indefinitely throughout the patient's life. The comprehensive procedure, encompassing detection to treatment and follow-up and comprises screening and diagnosis, staging, treatment planning and administration, treatment monitoring, and continuous surveillance. While histology is the definitive method for cancer confirmation, imaging is crucial for the diagnosis and therapy of cancer. A variety of imaging modalities, encompassing fundamental techniques such as X-rays, optical imaging, mass spectrometry, and photoacoustic imaging, as well as sophisticated technologies like sonography, computed tomography (CT), single-photon emission computed tomography (SPECT), positron emission tomography (PET), and magnetic resonance imaging (MRI), are employed for disease diagnosis and localization [7–15]. A chest X-ray is generally the primary instrument for detecting and localizing lung cancer, whereas mammography is employed for diagnosing breast cancer. Ultrasound is frequently utilized in the diagnosis of breast, prostate, and gynecological malignancies [7–12]. MRI and CT scans are essential in identifying cancers of the head and neck, as well as tumors in bone, soft tissue, and the brain [12–15]. PET/CT scans are very effective in diagnosing lymphomas and identifying distant metastases in multiple malignancies [16–18]. Imaging is essential for cancer staging, which entails evaluating the primary tumor, lymph node involvement (TNM classification), and distant metastasis. The TNM staging, derived from imaging and pathology findings, ascertains the cancer's overall stage and informs therapy choices [7–9].

This process generally necessitates a multidisciplinary approach, frequently integrating surgery, radiation, and chemotherapy, with the optimal treatment strategy established based on the stage and characteristics of the disease [5–9]. The significance of imaging in cancer diagnosis, staging, and treatment is paramount. Contrast-enhanced CT scans, referred to as planning CTs, are utilized in radiotherapy planning to outline the tumor and strategize treatment employing methods such as external beam radiation (EBRT) or brachytherapy (BT). Advanced radiotherapy devices, including tomotherapy, image-guided radiotherapy (IGRT), and intensity-modulated radiotherapy (IMRT), depend on these planning CTs for treatment simulations within a radiotherapy treatment planning system (TPS) [24]. These scans additionally function as a basis for radiomic feature extraction, as they encompass gross tumor volume (GTV) specified by specialists [25, 26]. Monitoring treatment and conducting follow-up are crucial for assessing treatment effectiveness and identifying adverse effects. Monitoring often entails assessing the patient's vital signs, hematological parameters, and alterations in imaging results. Imaging is especially valuable for monitoring disease regression or advancement during and following treatment [5–7, 15–17, 22–24].

Post-treatment follow-up is essential to evaluate the patient's overall health, the disease's status, and the likelihood of recurrence or advancement of cancer [16–21]. Blood tests are frequently employed to assess the patient's overall health and monitor disease development, whilst imaging is utilized to detect disease stability, local recurrence, or the existence of nodal or distant metastases [7–9]. Recurrence presents a frequent challenge during follow-up, necessitating restaging when it arises. This entails utilizing imaging and pathology results to evaluate the disease's condition and choose the most suitable treatment strategy [5–9, 21]. Imaging is essential in cancer management, significantly contributing to diagnosis, treatment, and follow-up care. It functions as a principal instrument for detecting the emergence of cancer and recognizing recurrence during subsequent evaluations. Multiple imaging modalities—including X-rays, ultrasonography, CT, MRI, SPECT, and PET—are utilized during the management process [20–24]. Advanced imaging modalities such as PET/CT, SPECT/CT, and PET/MRI are gaining prominence in holistic cancer management. This publication analyzes the roles of quantitative imaging and artificial intelligence (AI) in the advancing domain of oncology.

Quantitative Imaging:

Medical imaging findings can be classified into two categories: qualitative and quantitative factors. Qualitative parameters are influenced by the interpreter's perspective, whereas quantitative parameters are unaffected by such variability, providing greater consistency and dependability in clinical decision-making [27]. Historically, imaging data has been assessed qualitatively or semi-quantitatively for diagnostic and staging objectives. This method restricts the volume of information that may be derived from medical photographs. Visual inspection and semi-quantitative analysis offer merely a limited comprehension of the condition. Numerous essential details in medical photographs may not be readily discernible to the human eye but can be retrieved by mathematical and statistical techniques. Quantitative imaging transforms images into quantifiable traits that can be associated with significant therapeutic outcomes, such as tumor response to treatment in cancer management [25]. This transition to quantitative imaging provides a more objective and thorough method for comprehending illness progression. Traditional quantitative metrics employed in imaging encompass tumor size assessment using Hounsfield units (HU) in CT scans, standardized uptake value (SUV) quantification in PET scans, proton density and diffusion coefficients in MRI, and spectral peak values in MRI. These quantitative measurements have been capable of distinguishing between individuals who respond to treatment and those who do not [26–28]. For instance, Response Evaluation Criteria in Solid Tumors (RECIST) is frequently employed to evaluate therapy response by measuring tumor growth via CT scans, indicating anatomical alterations. PET Response Criteria in Solid Tumors (PERCIST) assesses therapy response by quantifying alterations in SUV values, hence offering insights into physiological modifications in tumors [31–35].

Radiomics:

Radiomics extends the notion of quantitative imaging, applying it within a wider framework. Radiomics is the extraction of several quantitative variables from medical pictures, facilitating a comprehensive assessment of therapy responses and clinical consequences [36]. This procedure yields more extensive data than traditional methods, delivering insights into diverse disease disorders and their correlation with patient outcomes [36–40]. Radiomic characteristics derived from medical images can be classified into many categories, such as shape-based features, first-order features, higher-order features, textural features, Laplacian-of-Gaussian (LoG) features, and wavelet features [37–41]. The radiomics methodology encompasses multiple stages, commencing with picture extraction and tumor segmentation, succeeded by preprocessing tasks including format conversion, voxel normalization, image masking, filtering, and transformation. The images undergo radiomic feature extraction from the original, filtered, and altered versions. The outcome is an extensive dataset that can be handled via feature selection or reduction techniques to ascertain the most pertinent characteristics. Ultimately, these chosen attributes are employed to construct prediction models that aid in therapeutic decision-making. Radiomics has demonstrated potential in enhancing customized cancer therapy by offering detailed and predictive insights into tumor dynamics, facilitating more accurate treatment planning and monitoring.

Artificial Intelligence and Big Data:

Artificial Intelligence (AI) denotes the creation of intelligent computers that can execute tasks usually necessitating human intelligence, including problem-solving, learning, and decision-making. Artificial Intelligence is propelled by two fundamental elements: Machine Learning and Big Data.

Big Data can be characterized by the 5Vs:

- Volume: Substantial quantities of data.
- Diversity: Information derived from several sources.
- Velocity: Accelerated data proliferation.
- Veracity: The quality and integrity of data.
- Value: The utility of the data in generating insights [43].

Machine Learning (ML) is a technique wherein machines acquire knowledge from previous data or occurrences, enhancing their performance autonomously without explicit programming. Machine learning algorithms are often classified into three primary categories:

- Regression Algorithms
- Decision Tree Algorithms

- Deep Learning (DL) Algorithms [44].

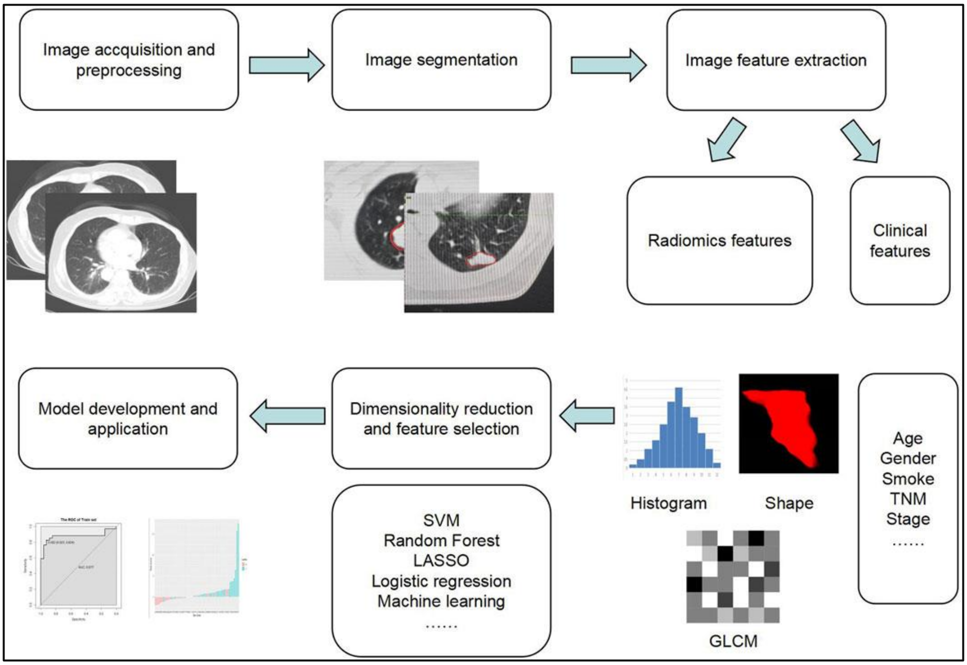

Figure 1: Application of Radiomics in Oncology.

Machine learning algorithms can be utilized by:

Supervised learning (labeled data), unsupervised learning (unlabeled data), or semi-supervised learning (a blend of labeled and unlabeled data) [44]. Deep Learning (DL) is a subset of Machine Learning (ML) that emphasizes algorithms acquiring knowledge from data via hierarchical feature representations, wherein intricate characteristics are derived from fundamental ones. Deep learning algorithms, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Artificial Neural Networks (ANNs), are utilized for intricate tasks such as image recognition and natural language processing. Choosing a suitable AI algorithm is essential and often relies on the specific task involved. Algorithms like logistic regression, random forest classifiers, and support vector classifiers are employed for binary or multi-class classification tasks. Linear regression, random forest regressors, and support vector machine regressors are utilized for predicting continuous or discrete outcomes. The efficacy of these models is assessed by predictive metrics including accuracy, precision, recall, F1-score, and Area Under the Curve (AUC), utilizing training and validation datasets.

Precision Oncology:

Remarkable advancements in cancer treatment include considerable enhancements in diagnostic and therapeutic apparatus, the creation of novel pharmaceuticals, and the refinement of surgical methodologies. Nonetheless, despite these developments, the success of treatments remains inconsistent, with certain therapies failing to get the expected results [56]. This has resulted in the development of personalized medicine in oncology, which customizes treatment approaches according to the unique attributes of individual patients and their conditions. Personalized oncology emphasizes the identification of patient subgroups within particular cancer types and the application of targeted therapies for those subgroups [57, 58]. This methodology is guided by the analysis of biomarkers and genetic alterations, which facilitate the categorization of patients for targeted therapy. In recent years, imaging biomarkers have been investigated to delineate patient subgroups and forecast treatment results [58, 59]. This transition to precision oncology facilitates customized treatment strategies designed to enhance outcomes and minimize superfluous side effects by aligning the appropriate therapy with the suitable patient at the optimal moment.

Limitations of Radiomics:

Radiomics encounters fundamental issues concerning repeatability and reproducibility, chiefly due to variability arising from discrepancies among scanners from different manufacturers, varied acquisition techniques, and intra-scanner variations. In our prior investigation of repeatability and reproducibility, we found that merely 10% of CT radiomic characteristics demonstrated acceptable repeatability and reproducibility across clinical cohorts and phantoms [60]. A comprehensive review by Traverso et al. [61] emphasized that the majority of radiomic characteristics exhibit stability issues. To resolve these challenges and unify radiomic extraction tools, features, and imaging protocols, multiple initiatives have been initiated by various organizations. The Quantitative Imaging Network (QIN) [62], the Quantitative Imaging Biomarkers Alliance (QIBA) [63], and Quantitative Imaging in Cancer: Connecting Cellular Processes with Therapy (QuIC-ConCePT) [64] are all committed to the standardization of imaging practices and biomarkers. The Image Biomarker Standardization Initiative (IBSI) aims for global harmonization of radiomic characteristics by reducing imaging disparities and standardizing the radiomic extraction method [65, 66]. QIN seeks to harmonize imaging parameters and hardware among various vendors, whereas QIBA has implemented scanning phantoms to evaluate and standardize variances between equipment models. The principal objective of these phantom investigations is to detect data gathering inaccuracies and formulate techniques to standardize imaging performance across different devices, hence reducing bias and variance among equipment. The initiatives undertaken by QIN may be crucial in the proper stratification of patients by the exact detection of imaging biomarkers [62]. Furthermore, the Radiomics Quality Score (RQS), introduced by Lambin et al. [37], seeks to tackle issues associated with the reporting of radiomic investigations. These activities are essential for promoting the standardization of imaging biomarkers.

Development of AI Infrastructure Employing the FAIR Data Principle:

Successful AI implementation in healthcare, especially in hospitals, necessitates the conversion of diverse data elements (including digital imaging and communication in medicine (DICOM), radiomic features, clinical data, diagnostic, pathology, and genetic information) into a findable, accessible, interoperable, and reusable (FAIR) format [67]. Data must be systematically organized and archived to provide accessibility for both humans and machines. This involves anonymizing the data and allocating global, persistent identifiers to guarantee effective data management. Furthermore, accessibility must be guaranteed by defined procedures for authorization and identification, enabling authorized individuals to effortlessly access the data. Linking various data formats to domain ontologies enhances interoperability among researchers, fostering a collective comprehension of the data. Reusability is enhanced by thorough documentation, which facilitates data interpretation among various user groups. These principles function as directives to augment data quality, emphasizing the enhancement of automation for effective data finding and reutilization. Oncology therapies produce extensive data that fulfill all five attributes of big data: volume, diversity, velocity, truth, and value. Such data are generally kept in many formats—spanning medical records in hospital systems to unstructured text entries or tables in hospital information systems (HIS)—which are not directly amenable to machine learning (ML). Converting and organizing this data into a machine-readable format poses considerable hurdles for data scientists [26]. There is an urgent necessity for the creation of automated systems capable of effectively converting and storing medical records in a manner suitable for machine learning.

Radiomics and Precision Oncology:

Multiple studies have underscored the crucial importance of radiomics in cancer therapy [59, 68]. The domain of radiomics has proliferated swiftly in the last ten years, with a multitude of articles illustrating its promise in cancer detection and treatment. A range of AI-based decision support systems (DSSs) utilizing radiomics has been created for cancer, demonstrating encouraging outcomes. Recently, a novel aspect of radiomics, termed delta radiomics, has become a central topic of investigation [69]. Delta radiomics entails the extraction and comparison of quantitative features from sequential scans acquired during treatment, yielding significant insights into treatment efficacy [69, 70]. Radiomic-based predictive models have been thoroughly evaluated in the diagnosis and management of several solid cancers. Literature indicates that radiomic features may function as quantitative biomarkers for various oncological conditions, including brain tumors, head and neck cancer, breast cancer, lung cancer, colorectal cancer, prostate cancer, gastrointestinal cancer, liver cancer, and cervical cancer [70–94].

Wang et al. [77] created a predictive model for responsiveness to induction chemotherapy based on MRI radiomic characteristics. Likewise, Sanduleanu et al. [78] developed a tumor hypoxia prediction model by integrating CT and PET radiomic characteristics. Tran et al. [79] developed a predictive model for neoadjuvant chemotherapy response in breast cancer via MRI radiomic characteristics, whereas

Park et al. [80] concentrated on forecasting disease-free survival in breast cancer by MRI radiomics. Zhang et al. [81] created a radiomic signature to forecast epidermal growth factor receptor (EGFR) alterations in non-small cell lung carcinoma. Huang et al. [84] developed a disease-free survival prediction model for early-stage non-small cell lung cancer (stages I and II) utilizing CT radiomics. Liu et al. [85] developed a radiomic model to forecast the response to neoadjuvant chemoradiotherapy in locally advanced rectal cancer. Shiradkar et al. [88] introduced an MRI-based radiomic model for predicting biochemical recurrence in prostate cancer. Altazi et al. [92] created a CT radiomic model to forecast treatment results in cervical cancer, whereas Reuzé et al. [93] anticipated the recurrence of cervical cancer utilizing a PET radiomic-based model. Chiappa et al. [94] combined transvaginal ultrasonography radiomics with serum cancer antigen 125 (CA-125) values to develop a decision support system for assessing the malignancy risk of ovarian tumors. Given the growing acknowledgment of radiomic characteristics as possible digital markers in precision oncology, future endeavors should concentrate on standardizing these parameters and discerning robust radiomic features as dependable digital biomarkers.

Prospective Plan:

The future of radiomics is contingent upon its practical use and incorporation into healthcare systems. A self-learning model may be built and deployed in healthcare environments to improve decision-making in decision support systems (DSSs). A heightened demand for tailored models to tackle particular clinical inquiries will emerge. Lambin et al. [37] propose that the current picture archiving and communication system (PACS) must transition into a picture archiving and radiomics knowledge system (PARKS) to accommodate the storage of radiomic signatures. The progression of AI-driven Decision Support Systems will be crucial in assisting doctors in making better informed judgments, thereby enhancing patient outcomes.

Other common Applications of Radiomics in Oncology:

Radiomics has a broad range of applications in oncology, extending beyond tumor diagnosis and treatment prediction. Below are some of the common ways radiomics is being applied in cancer care:

1. Tumor Characterization and Classification Radiomics allows for the detailed analysis of tumor characteristics, such as shape, texture, and heterogeneity, which can provide more information than traditional imaging techniques. By quantifying these features, radiomics can help differentiate between benign and malignant tumors, as well as identify specific tumor subtypes. For example, in **lung cancer**, radiomics has been used to predict histological subtypes and to classify tumors based on imaging features.

2. Treatment Response Assessment Radiomics has shown great promise in evaluating how well a tumor responds to therapy. By comparing radiomic features before, during, and after treatment, clinicians can assess the effectiveness of therapies, including chemotherapy, radiation, and immunotherapy. For example, studies have used radiomic features to predict **early treatment response** in **head and neck cancers** and **breast cancer**, helping to guide treatment adjustments.

3. Prognostic Prediction Radiomics can be used to develop predictive models for patient prognosis, such as survival rates or the likelihood of recurrence. These models are built by analyzing imaging features that correlate with clinical outcomes. For example, **glioblastoma** patients' survival predictions have been improved through radiomic models that consider features like tumor shape, edge irregularity, and texture.

4. Early Detection and Screening Radiomics offers potential in the early detection of cancers, especially when combined with advanced imaging modalities. In **lung cancer**, for instance, radiomic features from **CT scans** have been used to detect small nodules that may indicate early-stage tumors, potentially enabling earlier intervention and improving patient survival rates.

5. Prediction of Treatment Toxicity Radiomics can help predict the potential side effects or toxicities of treatments by analyzing changes in tumor and surrounding tissue characteristics. In **radiation therapy**, radiomic signatures from pre-treatment scans can forecast how patients will respond to radiation and whether they are at risk of developing side effects, such as radiation-induced lung injury.

6. Tumor Microenvironment Analysis Beyond analyzing the tumor itself, radiomics can also provide insights into the surrounding tumor microenvironment, including blood supply, tissue density, and immune cell infiltration. This is especially relevant in cancers like **prostate cancer**, where radiomic features from MRI scans have been linked to tumor vascularity and the presence of immune cells, providing insights into how tumors may grow or metastasize.

7. Metastasis Prediction Radiomic features can also be used to predict metastasis, the spread of cancer to distant organs. By analyzing the texture and shape of primary tumors and regional lymph nodes, radiomic models have been developed to predict the likelihood of distant metastasis in cancers such as **breast**, **colorectal**, and **melanoma**.

8. Personalized Treatment Plans By combining radiomic data with genomic and clinical information, oncologists can create personalized treatment plans tailored to the unique characteristics of each patient's tumor. In **rectal cancer**, radiomics has been used to assess the likelihood of response to chemoradiation, enabling more personalized and targeted treatment strategies.

9. Image-Guided Biopsy and Surgery Radiomic analysis can assist in the selection of biopsy sites or surgical approaches. By identifying regions within tumors that are most likely to yield accurate diagnostic information or harbor aggressive cancer cells, radiomics enhances the precision of biopsy sampling or surgical resection in cancers like **liver cancer** and **pancreatic cancer**.

In summary, radiomics is a rapidly evolving field that plays a pivotal role in enhancing the diagnosis, prognosis, and treatment of cancer, offering valuable insights into tumor characteristics, therapy responses, and patient outcomes. The integration of radiomics into clinical practice is poised to revolutionize oncology by improving precision medicine and facilitating more personalized care strategies.

Conclusion:

Radiomics has rapidly evolved as a pivotal tool in precision oncology, offering significant potential for improving cancer diagnosis, treatment, and monitoring. The integration of quantitative imaging with artificial intelligence (AI) allows for the extraction and analysis of complex patterns from medical images, far surpassing the limitations of traditional visual inspection. By transforming imaging data into actionable insights, radiomics aids in developing predictive models that can assess tumor response, monitor treatment progress, and identify recurrences, thereby facilitating more tailored and effective cancer treatments. A critical aspect of radiomics is its ability to capture a wide array of features from imaging modalities such as CT, MRI, and PET/CT, which can reflect underlying tumor heterogeneity and provide deeper insights into tumor biology. These features, including shape, texture, and intensity, are essential in assessing not only the anatomical characteristics of tumors but also their functional and molecular properties. Coupled with AI algorithms, particularly machine learning (ML) and deep learning (DL), radiomics can process vast datasets to detect subtle patterns that may not be visible to the human eye. AI models trained in these features can then predict patient outcomes, optimize treatment strategies, and help in patient stratification for personalized therapies. Despite its promise, the widespread clinical adoption of radiomics faces challenges, notably the variability in imaging data due to differences in acquisition protocols and scanner types. Such inconsistencies can affect the reproducibility and generalizability of radiomic features. To address these issues, several initiatives, such as the Quantitative Imaging Network (QIN) and the Image Biomarker Standardization Initiative (IBSI), are working towards standardizing imaging practices and radiomic extraction methods. These efforts aim to enhance the reliability of radiomics and its integration into clinical practice. In conclusion, radiomics, supported by AI, represents a transformative approach in precision oncology. While challenges in standardization and reproducibility remain, the future of radiomics holds great promise for advancing personalized cancer care, improving outcomes, and minimizing adverse treatment effects. With continued research and development, radiomics may play a central role in the next generation of oncology.

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دور الراديو ميكيات في الطب الدقيق للسرطان: مراجعة شاملة

الملخص:

الخلفية: يُعتبر السرطان اضطرابًا وراثيًا ناتجًا عن تكاثر الخلايا غير المنضبط، وهو أحد الأسباب الرئيسية للوفاة على مستوى العالم. تهدف التقدمات في الطب الدقيق للسرطان إلى تخصيص العلاجات بناءً على خصائص الورم الفردية، مما يعزز فعالية العلاج ويقلل من الآثار الجانبية. وقد ظهرت الراديو ميكيات، وهي استخراج البيانات الكمية من التصوير الطبي، كأداة قيمة في تشخيص السرطان وتخطيط العلاج والمراقبة. إن دمج الراديو ميكيات مع الذكاء الاصطناعي يعد بتخصيص استراتيجيات العلاج السرطاني بشكل أكبر.

الهدف: تهدف هذه المراجعة إلى استكشاف دور الراديو ميكيات في الطب الدقيق للسرطان، مع تسليط الضوء على تطبيقاتها ومنهجياتها وإمكاناتها في تحسين إدارة السرطان.

الطرق: تتناول المراجعة دور تقنيات التصوير المختلفة في الأورام، بما في ذلك الطرق التقليدية مثل الأشعة السينية والتقنيات المتقدمة مثل الرنين المغناطيسي (MRI) والأشعة المقطعية (CT) والتصوير المقطعي بالإصدار البوزيتروني (PET/CT) والرنين المغناطيسي .(MRI) وتناقش كيف تبني الراديو ميكيات على هذه

التقنيات لاستخراج الخصائص القابلة للقياس للنمذجة التنبؤية، مع التركيز على إمكانات الذكاء الاصطناعي والبيانات الكبيرة في تحليل هذه الخصائص. كما تعالج المراجعة دمج الذكاء الاصطناعي في الراديو ميكيات لتحسين قرارات العلاج السرطاني.

النتائج: توفر الراديو ميكيات تحليلاً أكثر شمولاً من التصوير التقليدي من خلال استخراج العديد من الخصائص الكمية مثل الشكل والملمس والكثافة. يمكن للنماذج المدفوعة بالذكاء الاصطناعي باستخدام هذه الخصائص التنبؤ بنتائج العلاج، وتقييم استجابة الورم، وتحديد احتمال تكرار المرض. تناقش المراجعة تقنيات الذكاء الاصطناعي، بما في ذلك التعلم الآلي (ML) والتعلم العميق(DL) ، وتطبيقاتها في تحسين دقة علاج السرطان .

الاستنتاج: إن دمج الراديو ميكيات مع الذكاء الاصطناعي في الطب الدقيق للسرطان يحمل وعودًا كبيرة لتحسين تشخيص السرطان وعلاجه ومراقبته. ومع ذلك، يجب معالجة التحديات مثل التباين في بروتوكولات التصوير وإمكانية التكرار ليتم تطبيق الراديو ميكيات بشكل أوسع في البيئات السريرية .

الكلمات المفتاحية: الراديو ميكيات، الطب الدقيق للسرطان، التصوير، الذكاء الاصطناعي، علاج السرطان، التعلم الآلي، التعلم العميق، المؤشرات الحيوية التصويرية، استجابة الورم.