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New Trends in Cancer Treatment With Multimodality Imaging Techniques and Applications

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Abstract

Advances in multidisciplinary imaging have revolutionized the early detection, management, and treatment planning of cancer. This review focuses on the fusion of imaging with cross- disciplinary technologies, such as radiomics and artificial intelligence (AI), that collectively help provide a full characterization of tumor properties. The combination of imaging with laboratory results, genomic findings, and clinical data may facilitate accurate staging and patient-centered treatment allocation. Therapeutic and screening programs guided by images have shown significant potential to reduce mortality and treatment toxicities. This review emphasizes the need for academia, biotechnology, and pharmaceutical industries to collaborate synergistically in order to continually introduce new developments in cancer imaging. Future progress in the interdisciplinary combination of imaging science and technological development will further geometrically enhance our diagnostic potential, therapeutic control efficacy, the oncological patient's tolerance, and treatment outcomes for cancer disease processes, with AI-guided techniques increasingly becoming a core contributor to improved precision oncology, along with better overall patient care.

Keywords: Advanced Cancer Care, Multimodality Imaging, Image Processing, Diagnosis And Therapeutics, Radiomics, Artificial Intelligence, Precision Oncology Imaging-Guided Therapy

1. Introduction

Cancer continues to be one of the most prevalent causes of morbidity and mortality globally, necessitating the need for new methods for early detection, accurate staging, and personalized treatment [1]. Classical diagnostic procedures have experienced overwhelming developments during the last decades, particularly with the development of multimodal imaging approaches taking advantage of complementary imaging modalities to perform an in-depth tumor characterization. The fusion of several modalities [1, 2], mainly magnetic resonance image (MRI), computed tomography (CT), positron emission tomography (PET) and single photon emission computerised tomography known as SPECT, has been a breakthrough in oncology. These techniques, when combined in a complementary manner, can overcome technique- specific limitations and offer an anatomical as well as functional information necessary for clinical management.

Cancer care change is not limited to the traditional imaging interfacing. State-of-the-art oncology practices have seen an increase in the use of advanced computational approaches, such as radiomics and artificial intelligence (AI), for extracting quantitative imaging parameters from medical images to yield objective tumor characterization [3]. The integrated multimodality imaging co-registered with AI analysis reflects a significant step towards precision medicine, where doctors can make personalized treatment decisions for their patients based on the full spectrum of the patient's tumor biology]. In this review article, the multimodality imaging paradigm in cancer care is outlined, the latest technical breakthroughs such as radiomics and AI efforts are explored, from a clinical perspective practical applications yet stratified on specific tumor entities or clinical care situations reported and future directions have been identified to further proceed steps towards more personalized oncologic medicine.

2. Multimodality Image Reconstruction in Cancer Diagnosis

2.1 Complementarity of the Individual Imaging Techniques

Both imaging modalities provide distinct diagnostic information to be included into a comprehensive tumor evaluation. Computed tomography (CT) permits excellent anatomic detail resolution and short acquisition times for the detection of solid masses and characterization as well as tumor staging [5]. The higher soft tissue contrast as well as multiparametric nature of MRI allows the assessment of tumor invasion, peritumoral edema and proximity to critical structures in greater detail, particularly important in diseases like rectal cancer and brain tumors [6]. Positron emission tomography (PET), especially with an 18F- labelled glucose analogue (FDG, fluorodeoxyglucose) provides metabolic information describing glucose consumption patterns which are typical for malignant tissue and allow detecting distant metastases and offers the possibility of monitoring treatment response [7].

The inherent shortcomings of each single-imaging modality have long been recognized by the clinical community. CT provides superior detection capabilities of macroscopic disease but relatively poor soft tissue contrast and therefore the ability to miss small lesions with low metabolic activity [8]. Despite its better soft tissue discrimination, MRI has the disadvantage of being a time-consuming modality and is not indicated in patients with metal implants [9]. The PET/CT has a high metabolic sensitivity and limited anatomic specificity and is unable to identify subtle morphologic changes 10]. These mutual limitations justify in principle multimodality approaches, where the joining information (from imaging) improves diagnostic performance and clinical value as compared with sole-modality assessment [11].

2.2 Hybrid Imaging Platforms

Hybrid imaging systems have been a technological leap forward that allows integrated multimodality assessment. PET/CT allows PET metabolic information to be combined with CT anatomical detail, facilitating precise localization of metabolic abnormalities and better characterization of indeterminate findings [12]. Addition of PET/MRI provides further benefits via metabolic and superior imaging soft tissue signature in turning out as a potent approach for lesion evaluation. [13] Newer series have shown that PET/MRI offers better performance than conventional PET/CT in defined clinical indications, especially for lymph node staging and identification of complex lesions [14].

The relative performance of multimodalities across different platforms varies with clinical circumstance and type of disease, as indicated by comparative studies. In breast cancer nodal staging, PET/MRI was able to detect significantly more lymph node metastases as compared with CT or MRI alone [14]. In terms of prostate cancer staging, PSMA PET/CT was more accurate than multiparametric MRI by itself in detection lymph node metastases [15]. These results highlight the need to use multimodality imaging strategies according to specific clinical questions and disease biology. The era of hybrid imaging systems has rapidly evolved from research tools to clinically established techniques for comprehensive oncological assessment [16].

3. The Key to Precision Oncology?

3.1 Basics of Radiomics and Feature Extraction. First-order statistics describe the distribution of intensity values within the image.

Radiomics is a methodological revolution away from the qualitative visual perception to quantitative features of imaging functions from medical image processing [3]. This computable method allows for the quantitatively analyzing imaging texture, morphology, and intensity patterns to describe tumor heterogeneity and predict biology. The radiomics pipeline initiates from image acquisition under standardized protocols for consistency and reproducibility, tumor delineation to inform regions of interest (ROI) for feature extraction [17]. Feature extraction then produced several hundred quantitative image descriptors that can include first-order statistics, shape based and texture based characteristics of the tumor microenvironment [18].

Feature selection is an important part in radiomics, which includes the process of finding a subset of optimal imaging biomarker components from all feature dimensions [19]. Selected features are then utilized by machine learning algorithms, such as logistic regression, random forest and support vector machines to construct predictive models for clinical outcomes [20]. The reproducibility of radiomics features has been established by multicenter standardization efforts, namely the Image Biomarker Standardization Initiative (IBSI) that includes standardized definitions and validated reference values guaranteeing uniformity across various software platforms or institutions [21].

3.2 Radiomics in Cancer Diagnosis and Prognosis

Radiomics is widely recognized to have great potential for improving diagnostic accuracy in various types of cancer. In lung cancer, radiomics analysis on CT imaging enhances the differentiation between benign and malignant nodules [22], and machine learning models yield diagnostic performance superior to that of conventional radiologic review [20]. radiomics of breast cancer allows for the non-invasive prediction of molecular subtypes, androgen receptor status as well as HER2 positivity/mutational status in some patients [23]. Radiomics in prostate cancer can predict clinically significant disease and Gleason score aiding treatment selection [24].

The prognostic roles of radiomics have shown much clinical value, providing predictive information of treatment responses, progression-free survival (PFS), and overall survival (OS) in various types of cancers [25]. Rectal cancer radiomics can detect high-risk patients with the high probability of disease recurrence, which help to emphasize on this group [26]. Glioma radiomics is able to predict both survival time as well as molecular features including IDH1 mutation status and MGMT methylation status, genetic markers with profound implications for treatment [27]. These prognostic abilities reflect the role of radiomics in aiding risk stratification and personalized treatment decision-making, which are fundamental for precision oncology [28].

4. Artificial Intelligence and Deep Learning in Cancer Imaging

4.1 Machine and Deep Learning Architectures

Especially, AI technologies such as deep learning have dramatically changed the paradigm of automated medical image analysis and reporting [29] in terms of object (or abnormality) detection, classification, or segmentation with performance comparable to or even better than that of expert clinicians. The methods based on Convolutional Neural Network (CNNs), which is the cornerstone of medical image analysis could automatically learn hierarchical feature representations from raw imaging data rather than manual feature design[30]. Novel architectures such as Vision Transformers (ViTs) and ensemble learning exhibited better performance, especially for complex segmentation and classification problem [30].

Transfer learning is a powerful method that can be applied to adapting AI models trained on large, general imaging sets of data to specific cancer imaging tasks, which is important since in many cases we have only small amounts of labeled cancer imaging samples [20]. Generative adversarial networks (GANs) are capable of providing realistic synthesis of medical images, and could thereby assist in data augmentation for model generalization [31]. Attention mechanisms, which allow models to selectively attend clinical relevant regions have significantly improved interpretability and clinical relevance of AI predictions [32].

4.2 AI-Driven Cancer Imaging in Clinical Practice

AI in cancer imaging is used across the spectrum from diagnosis to treatment. For screening and early detection, AI exhibits superior sensitivity and specificity in the detection of lung nodules, mammographic abnormalities, and colorectal polyps for initial evaluation [33]. In terms of diagnosis and staging, AI systems benefit from the increased accuracy with which tumors can be classified, staged, and assessed for presence of distant metastases [34]. Treatment planning in radiotherapy and surgery benefits from AI-augmented target delineation, decreasing planning time and increasing consistency [35].

Machine learning models can predict treatment response to chemotherapy, immunotherapy and targeted agents – enabling personalized therapy selection based on imaging phenotypes and biological features [36]. Radiomics and AI predict response to immunotherapy in lung cancer, zeroing in on who will benefit from checkpoint inhibitors [33]. Deep learning-based histopathology image analysis can be used for the prediction of genetic alterations and biomarker status, enabling a new concept of image-derived molecular profiling [37]. The various clinical applications indicate the paradigm of AI as a revolutionary tool in enhancing diagnosis, providing personalized therapy, and improving patient outcomes [29].

5. Multimodal Data Integration for Pancreatic Tumor Characterization

5.1 Imaging-Genomic Integration

The integration of imaging with genomics and proteomics is a forefront in precision oncology, allowing the multilevel characterization of tumors [38]. Radiogenomics (ie, the correlation between imaging features and genomic alterations) shows that specific imaging features represent underlying molecular biology and correlate with genetic changes [27]. In lung cancer, radiomics signatures can predict exon 19 deletions and L858R mutation status of EGFR, which affect the ability to predict targeted therapy response [20].

Combining multiomics and imaging features using AI can predict treatment response and patient's prognosis better than using single modality studies-genomics, transcriptomics, proteomics or metabolonomics [38]. Deep learning models that consider multiple omics data achieve much higher diagnostic accuracy and prognostic performance than those based on single omics type

[39]. Such integration demands advanced data harmonization that includes handling of technical variability and imputation of missing data, issues currently being tackled by state-of-the-art machine learning algorithms [39].

5.2 Deep Learning on Multimodal Fusion

The AI solution can provide devices with the capability of data-modalities fusion in addition to single modality information analysis which is currently impossible. The first is feature-level fusion, which integrates imaging radiomic features and genomics data at the beginning of the analytical process, and the second is decision-level fusion, which combines separate predictions from each modality [40]. Graph neural networks represent interrelations among mixed data (i.e., nodes) and transformer-based architectures achieve cross-modal fusion using attention mechanisms [39].

Clinical application of multimodal AI fusion holds great potential. A multimodal machine learning model for predicting biochemical recurrence of prostate cancer outperforms single modality models [41]. Integration of imaging, clinical and molecular data with AI can predict treatment response for various cancer types [42]. Such multimodal manner frictionlessly captures the practice of experienced oncologists, which empowers the design and implementation of AI-driven clinical decision support solutions [43].

6. Image-Guided Therapeutic Interventions

6.1 Image-Guided Surgery and Radiotherapy

Imaging guidance has become an integral part of the delivery of treatment for cancer in the modern era, where it has helped to improve target accuracy and reduce off-target toxicity. Real- time intraoperative imaging has been introduced that allows for visual control over tumor margins and important structures, which can help with more complete resection of the tumor while sparing the vital structures [44]. Fluorescencent-guided surgery with tumor-targeting fluorescent contrast agents increases detection of cancerous tissue, which can aid in achievement of higher degree of resection and reduce positive margins [44].

With this goal, radiotherapy planning in clinical routine is relying more and more on the use of multimodality imaging for precise visualization of targets. PET/CT-based planning better draws the boundary of involved lymph nodes than CT alone drawing, thus, reducing geographic miss while sparing normal tissue [45]. MRI-guided radiotherapy allows daily adaptive replanning based on anatomic changes during treatment, which may result in enhanced local control and reduced toxicity [46]. Image guidance during radiotherapy delivery with cone-beam CT verification provides accurate positioning and facilitates adaptation of treatment in real-time [47].

6.2 Assessment of Response and Toxicity to Treatment

Such multimodality tracking studies will provide longitudinal assessment on treatment efficacy for guiding whether therapy suspension, conversion, or cessation. Functional imaging based on a combination of diffusion-weighted MRI and dynamic contrast-enhanced sequences is capable to predict chemotherapy response prior to morphological alterations for an early identification of non-responders [48]. PET is more sensitive than CT in detection of treatment failure and intervention can be performed at an earlier stage [49].

Image-based evaluation of treatment-related toxicity is employed for any supportive care intervention or treatment modification. Imaging allows detection of radiation-induced changes in normal tissue distinguishing it from recurrent disease and predicating prognosis [50]. Advanced imaging biomarkers may be used to predict immunotherapy-related toxicity for the purpose of identification of high-risk patients, who need more close monitoring and prophylactic measures [51].

7. Clinical Applications Across Cancer Types

7.1 Lung Cancer: Screenings, Precision Medicine.

From low-dose CT screening through treatment planning and surveillance, multimodality imaging has an enormous impact on the way we manage lung cancer today. AI-augmented CAD systems enhance nodule detection and classification in screening CT and show increased sensitivity and specificity [33]. PET/CT can assess the risk for malignancy of pulmonary nodules and thereby decrease unnecessary biopsies and increase appropriate workup of malignant lesions [7]. Multimodal imaging offers the necessary staging truthfulness for treatment planning, with PET/CT leading to an increase in the detection of a dissemination as well as involved mediastinal lymph nodes [52].

Baseline CT radiomic features can predict response to treatment with immunotherapy and targeted therapies, thereby allowing personalized selection of therapy [33]. Radiomics combined with genomics-enabled prediction of EGFR and other driver mutations for selection of targeted therapies [20]. Early integration of imaging, clinical and molecular information by ML models maximizes treatment selection and survival predictions [53].

7.2 Breast Cancer Diagnosis and Risk Estimation continued May 2005: of different units are associated with the hazards for developing in situ breast cancer.

Multimodality imaging techniques result in a significant benefit for the diagnosis, planning of treatment and follow up of breast cancer. Multiparametric MRI identifies additional foci of cancer that are not seen on mammography and alters clinical management by determining who is suitable for breast conservation versus mastectomy [54]. In contrast-enhanced spectral mammography, anatomic mammographic detail is combined with functional vascular information, leading to increased specificity for the differential diagnosis between benign and malignant lesions [55].

MRI-based radiomics analysis detects phenotypic heterogeneity predicting molecular subtype, response to treatment, and prognosis [23]. AI-based multimodality imaging analysis predicts pathologic complete response to neoadjuvant chemotherapy and helps in classifying patients as those who would be benefit from enhanced treatment or require de-escalation of therapy in excellent responders [56]. Machine learning models that incorporate imaging, clinical and molecular data are able to predict treatment toxicity and long-term outcomes, which aids the development of individualized management strategies [57].

7.3 Prostate Cancer: Patient Side Personalized Diagnostics and Treatment Planning

Multiparametric MRI (mpMRI) has transformed the diagnosis of prostate cancer, identifying clinically significant disease to enable avoidance of biopsy in benign cases. Combining PSMA-targeted PET with MP-magnetic resonance imaging (MRI) helps both detection of primary cancer foci and finding the distant metastasis over each modality alone [58]. Combining the two imaging modalities for fusion-targeted biopsy increases detection of cancer and decreases the number of unnecessary biopsies [59].

Radiomics of mpMRI is predictive on Gleason score, biochemical recurrence and hormonal treatment response [24]. Integration of imaging data with genomics and clinical features using AI facilitates the prediction of toxicity and long-term outcomes from treatment [60]. There is a hope that image-guided focal therapy strategies, such as multimodality imaging for accurate targeting of dominant intraprostatic lesions with sparing of normal tissue, show potential in decreasing treatment consequences for patients but still preserving cancer control [61].

7.4 Rectal Cancer: Improving staging and Evaluation of Treatment Response

Trimodality imaging with MRI and PET/CT has revolutionized rectal cancer care by predicting response to treatment and for accurate staging. MRI is used to determine tumor penetration depth and nodal involvement, as well as its association with vital structures such as mesorectal fascia which influence surgical management [6]. The addition of PET/CT increases distant metastases detection rate compared to CT alone and prevents inappropriate surgery in patients with locally advanced tumor [45].

A radiomics approach applied to baseline MRI is useful for predicting which patients will not respond to neoadjuvant chemoradiation vs. those that do and can be used for treatment escalation or de-escalation [26]. Machine learning algorithms that integrate imaging with clinical and genomic information enhance prediction of response to treatment and prognostication [62]. These predictive capabilities can pave the way for tailored strategies of neoadjuvant therapy with avoidance of unnecessary surgery in complete responders, whereas intensification for non-responders [63].

8. Precision Medicine and AI-Assisted Clinical Decision Support Predictive analytics play an important role in precision oncology.

8.1 AI to Support Treatment Decisions

Modern practice increasingly uses AI-based decision support systems that incorporate information from multimodality imaging and genomics as well as clinical details with which to make treatment choices. These systems integrate complex relationships among imaging phenotypes, molecular alterations and treatment response to help predict the right therapy for the right patient [64]. Machine learning systems that learn from large clinical trial datasets encode the associations between patient characteristics and treatment responses to predict which therapies are most likely to benefit individual patients [4].

OncoGPT and other AI-based platforms provide a proof-of-concept that the deep learning model can be used to integrate NGS data with patients' clinical, which help us to discover clinically relevant mutations and pair patients with targeted therapies or the most suitable clinical trials [65]. These systems markedly improve the proportion of patients assigned to effective treatments as compared to traditional biomarker-driven approaches, and hazard ratios in favor of AI-selected treatment have been reported [65]. For widespread clinical use, these systems would need to interface with current electronic health records and have workflow considerations in place to maximize their utility [43].

8.2 Biomarker Identification and Patient Stratification

AI-based biomarker discovery uses imaging, genomic, and clinical data to discovered new predictive and prognostic signatures that enhance patient risk stratification [66]. Radiogenomics which combines imaging phenotypes with genomic alterations, allows prediction of molecular features from imaging alone and provides a route towards non- invasive molecular profiling [27]. Integrated machine learning models use multi-modality data types to predict treatment response, toxicity, and long-term outcomes more accurately than single-function models [42].

Federated learning methods allow AI models to be collaboratively developed across different institutions without the need for centralized data sharing, dealing with privacy issues and offering advantages in terms of model generalization capability [67]. This systematic approach results in expedited model validation and clinical deployment, and at the same time maintains institutional autonomy and patient privacy [67].

9. Challenges and Future Directions

9.1 Technical and Methodological Challenges

In the last several decades, there has been dramatic advancement in multimodality imaging and AI-enabled cancer care; however, a number of technical challenges hinder its wide clinical application. Data harmonization across institutions and imaging platforms is still a large challenge, and both the acquisition protocols/reconstruction algorithms and the image characteristics affect radiomics reproducibility to a great extent [68]. Feature diversity and unstable performance of AI models on distinct populations and imaging equipment motivate a strong external validation before clinical application [68].

Model interpretability and explainability are key missing pieces, as most deep learning models are "black box" solutions that generate predictions without clear rationale, which hampers clinical acceptance and regulatory approval [64]. Implementation of AI systems into the workflow is faced with practical challenges such as computational demands, data security and regulatory aspects [69].

9.2 Post-processing and New Trends

Advanced AI frameworks such as large language models and multimodal transformers present at least theoretical potential for higher integration performance of heterogeneous data types in the clinical context [70]. Federated learning and privacy preserving machine learning would allow joint model training while protecting patient confidentiality[67]. The merging of online imaging guidance with AI treatment planning will allow adaptive radiotherapy and image- guided surgery to be performed in ways that were unthought-of until now [50]. Non-invasive liquid biopsy with imaging and AI may allow early diagnosis and holistic, less invasive follow up of the tumor [71]. Further investment in standardization efforts, multicenter collaborations, and regulatory considerations is needed to facilitate translation of emerging preclinical findings into clinical use [69].

10. Interdisciplinary Collaboration and Industry Partnership

10.1 Academic-Industry Collaboration for Innovation

Such initiatives require ongoing cooperation between centres of academia, biotech industry and pharmaceutical companies for momentum to be gathered in cancer imaging innovation. Academic science creates basic scientific understanding and proves new imaging methods in stringent trials. Biotech companies create new imaging hardware, software, and contrast agents that move academic findings into practical clinical tools. Advanced imaging biomarkers are incorporated by pharmaceutical developers during drug development processes for precision identification and real-time monitoring of the drug effectiveness [64].

Public-private partnerships encourage corporate investment in areas of high risk, for example, image standardization, software creation and clinical validation where the return on investment would not necessarily be acknowledged without government intervention. Regulatory cooperation between agencies, academic researchers and industry partners expedites regulatory pathways for new imaging biomarkers and AI systems with considerations for patient safety and effectiveness [69].

10.2 Data Sharing and Open-Science

Open-access imaging databases such as The Cancer Imaging Archive, LIDC-IDRI, and others have accelerated AI research by offering standardized annotated imagery for algorithm development and testing [20]. Collaborative efforts to implement a consistent imaging protocol and standardize definitions of radiomic features enables reproducibility and comparison of results across institutions [68]. Solutions International consortia dedicated to specific cancers exchange knowledge and data, speeding up biomarker discovery and clinical validation [69].

11 Regulatory and Clinical Implementation Framework

11.1 Regulation on AI Based Imaging

Regulators from around the globe are currently drafting frameworks for testing and approving AI systems in medical imaging. The FDA's approach stresses clarity of algorithms, shown general applicability in various populations and imaging hardware, and clear clinician validation with patient benefit [72]. Regulatory but adaptive pathways allow the approval of AI systems that are under continued real-world validation and iterative refinement, recognizing fast technological changes [72].

Standards for AI reporting or guideline on the design and implementation of AI in clinical medicine are also available, e.g., TRIPOD+AI statement to ensure transparency in methodology, validation and performance characteristics which can be reproducible and used by peer review process or implementation into clinical practice [72]. These regulatory paradigms must align encouraging innovation with ensuring patient safety, allowing beneficial technologies to be translated quickly and inhibiting early clinical practice of unvalidated systems [69].

11.2 Clinical Utility and Health Economics

Integration into clinical system for daily practice and optimal workflow Implementation of advanced multimodality imaging systems with AI needs successful integration into healthcare providing a new way to deliver patient care paving the road for triage. Adherent to any training regimens for radiologists, oncologists and other clinicians will be understanding the interpretation of complex multimodal datasets, and appropriate use of AI generated recommendations [64]. Health economics studies that provide evidence for improved patient outcomes and cost savings are critical to reimbursement and institutional integration [47].

Actionable challenges include equitable access to advanced imaging and AI-powered precision oncology, which are often limited to resource-advantaged regions. Scalable and cost effective solutions transferrable to resource-poor health care systems are necessary if significant global gains in cancer outcomes are to be achieved [73].

Conclusion

Multimodality imaging integrated with emerging technologies, such as radiomics and artificial intelligence has the potential to revolutionize cancer diagnosis, therapeutic planning, and surveillance. Fusion of complementary imaging modalities bypasses individual limitations and enables comprehensive tumor biology characterization which is crucial in precision oncology [1]. Radiomics allows us to quantitatively measure imaging features related to tumor heterogeneity and predicting biological behavior in an objective manner [3]. AI based analysis combines multimodality imaging and genomic, proteomic, and clinical information to support precise patient stratification and treatment selection [4].

Multimodality image guidance has significantly facilitated image-guided therapeutic interventions, such as surgery and radiotherapy, leading to more accurate targeting and reduced normal tissue toxicity [44]. Such multi-modality approaches have application for a range of cancer sites, from lung cancer screening to rectal cancer treatment planning and now with increasing evidence for their potential impact on patient outcome [64]. Further progress will demand continued investment in technology development, standardization efforts, robust clinical validation and interdisciplinary interactions between academic, biotechnology and pharmaceutical stakeholders.

In the future, continued success followed should be dependent on successfully addressing these remaining challenges — data harmonization, model generalisability and interpretability and possible policy into equitable access. Application of such technologies goes beyond AI for RT, to embrace LL models, quantum computing and adaptive radiotherapy with intelligent treatment planning (51), which offer the potential for further gains in both diagnosis and therapy sensitivity. The use of actionable genomics in precision oncology practice needs to be underpinned by regulatory paradigms that facilitate timely translation of well validated advances,with patient safety as the paramount consideration. By working together across academia, industry and regulatory agencies, multimodality imaging combined with AI-based analytics is a promising approach to make a significant impact on cancer outcomes and accelerate the transformation of oncologic practice towards truly personalized, effective and equitable cancer care [69].

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