PET Imaging and Radiotherapy: A Survey of Multidisciplinary Approaches in Modern Cancer Management

Abstract

This survey comprehensively examines the integration of PET imaging, biological guide radiotherapy, adaptive radiotherapy, radiation oncology, molecular imaging, and personalized cancer treatment, highlighting their roles in modern cancer management. PET imaging provides critical metabolic and functional insights, enhancing diagnostic accuracy and treatment planning. Biological guide radiotherapy leverages biological markers for precision dosing, while adaptive radiotherapy allows real-time treatment adjustments based on tumor dynamics. Molecular imaging complements these approaches by elucidating cellular processes, informing personalized treatment strategies. The survey explores advancements in AI and machine learning, which enhance imaging quality and facilitate treatment customization. Challenges such as noise reduction, data integration, and clinical implementation are addressed, with solutions proposed to optimize therapeutic outcomes. Future directions emphasize the development of robust AI models, novel imaging biomarkers, and personalized treatment regimens. By synthesizing these multidisciplinary technologies, personalized cancer treatment aims to tailor interventions to individual patient characteristics, improving efficacy and patient outcomes. This survey underscores the transformative potential of these integrated approaches in advancing precision oncology.

1 Introduction

1.1 Structure of the Survey

This survey systematically explores multidisciplinary approaches in modern cancer management, focusing on the integration of PET imaging, biological guide radiotherapy, adaptive radiotherapy, radiation oncology, molecular imaging, and personalized cancer treatment. The initial sections establish a foundational understanding of core concepts and technologies, elucidating their roles and interconnections in cancer management. Subsequent discussions delve into the principles and mechanisms underlying each technology, emphasizing their contributions to improved treatment outcomes.

The significance of PET imaging in cancer management is thoroughly examined, particularly its role in diagnosis, treatment planning, and monitoring response. Recent advancements, such as low-dose imaging and AI integration, are highlighted for their impact on diagnostic accuracy and treatment planning [1]. The survey then transitions to biological guide radiotherapy, analyzing the potential of precision dosing based on biological markers to enhance treatment precision and outcomes.

A detailed examination of adaptive radiotherapy follows, emphasizing its capacity to modify treatment plans in real-time in response to changes in tumor size or position, bolstered by recent technological advancements [2]. The integration of molecular imaging with radiation oncology is also explored,

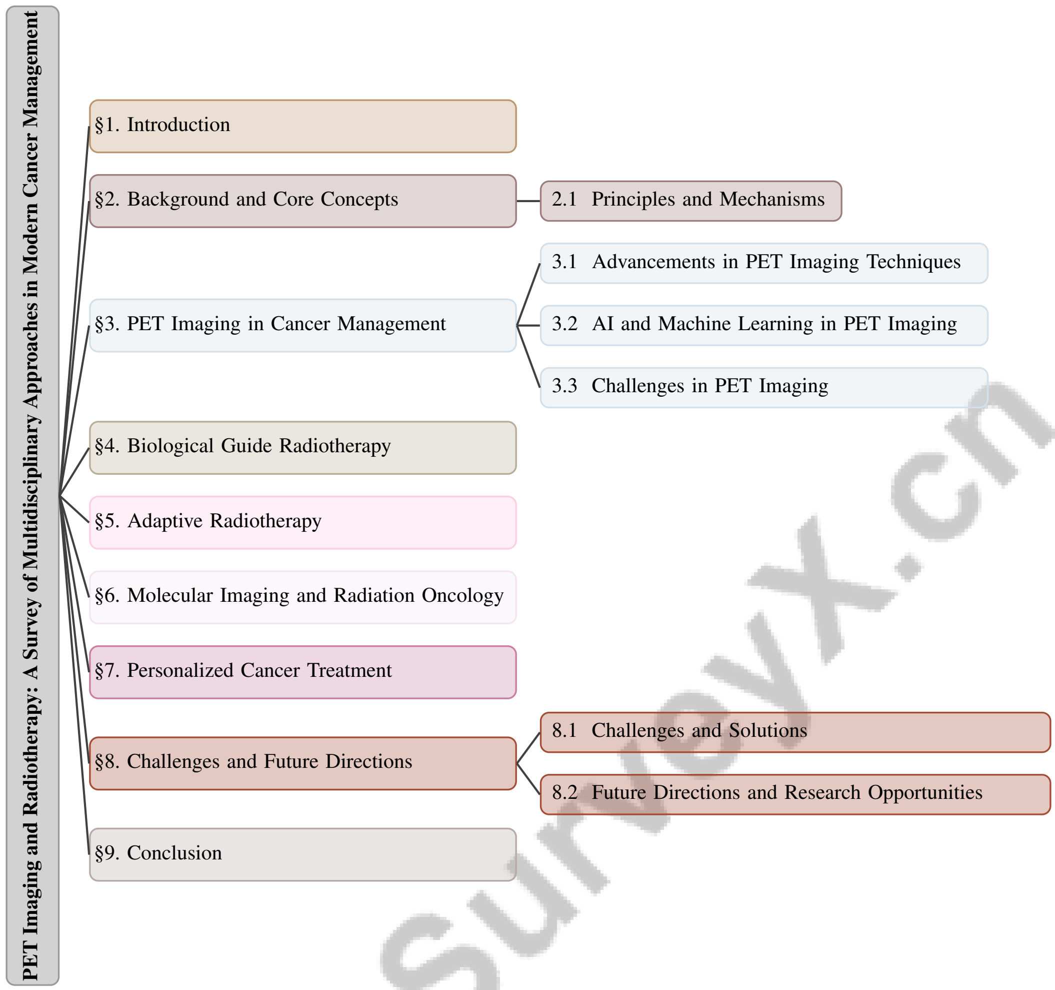

Figure 1: chapter structure

demonstrating how insights into cellular processes and tumor biology enhance radiation therapy practices.

The discussion culminates with an exploration of personalized cancer treatment, focusing on how the integration of these technologies tailors therapeutic strategies to individual patient characteristics for improved outcomes [3]. The role of AI and data-driven approaches in customizing treatment is considered, alongside challenges and future directions for implementing these multidisciplinary strategies in clinical practice. Potential solutions and research opportunities to further advance cancer treatment are also identified [4].The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Principles and Mechanisms

The integration of PET imaging, biological guided radiotherapy, adaptive radiotherapy, radiation oncology, molecular imaging, and personalized cancer treatment forms a comprehensive framework for modern cancer management, enhancing therapeutic outcomes. PET imaging is crucial for detecting metabolic and functional tumor changes. Techniques like Dynamic Segmentation for PET Images (DSPET) and DeepPET, which employs a deep convolutional encoder-decoder network, improve pharmacokinetic parameter extraction and image quality [5, 6]. The suDNN approach enhances PET image reconstruction using multimodal inputs, including low-count PET and MRI images [7]. Despite these advancements, parameter estimation in kinetic models remains challenging due to high noise levels [8]. Methods like Pitch-In, which uses third-order Hermite interpolation, improve image quality while preserving temporal dynamics [9]. The CLR 124/131 theranostic approach combines CLR 124 and CLR 131 with PET/CT imaging for improved tumor targeting and treatment [10]. Dual-channel deep learning architectures for PET attenuation correction and TGV regularization further enhance image fidelity and address the ill-posed inverse problem in PET imaging [11, 12].

Biological guided radiotherapy personalizes radiation doses using biological markers, with PSMA ligand PET imaging showing high sensitivity and specificity for prostate cancer [13]. This personalization is crucial for optimizing treatment precision, as demonstrated by radiation dose de-escalation studies based on functional imaging assessments of tumor hypoxia [14]. The I-PREDICT method uses genomic profiling to guide personalized combination therapies, addressing multiple molecular alterations for enhanced efficacy [15]. Understanding radiobiological effects, particularly the impact of high ionizing radiation doses on tumor control and normal tissue toxicity, is vital for refining radiotherapy strategies [16]. Evaluating various DIR algorithms under different deformation scenarios is essential for refining radiotherapy techniques [17].

Adaptive radiotherapy improves treatment through real-time plan adjustments based on tumor dynamics. Advanced imaging modalities like MRI introduce complexities in dose measurement, requiring solutions to mitigate magnetic field influences [18]. AI and machine learning integration in adaptive radiotherapy aims to optimize processes and improve outcomes amidst clinical data complexities [19]. Techniques like simultaneous denoising and motion estimation using a Siamese network architecture enhance adaptive radiotherapy precision by mapping low-dose gated PET images to high-dose equivalents [20]. Machine learning integration into radiation oncology workflows further improves patient outcomes and operational efficiencies [21].

Molecular imaging complements radiation oncology by elucidating cellular processes. Granzyme B PET imaging serves as a predictive biomarker for immunotherapy response, aiding in precise treatment decisions [22]. Novel techniques like IH-XPCT combine X-ray phase contrast tomography with immunohistochemistry to provide insights into tumor biology by visualizing specific cells in their context [23]. Immunotherapy strategies in radiation oncology, categorized into passive and active approaches, advance treatment options [24]. NLP models that classify clinical texts and recognize named entities facilitate the integration of vast clinical data into treatment strategies [25]. RadOnc-GPT, a large language model fine-tuned for radiation oncology tasks, aids in generating treatment regimens and providing diagnostic descriptions [26].

Personalized cancer treatment synthesizes these technologies to tailor interventions based on individual patient characteristics. Challenges include individualizing treatment amidst complex genetic, environmental, and physiological interactions [3]. Automated lesion segmentation in PET/CT scans is crucial for improving clinical workflows and advancing diagnostics [27]. The radiomics process, structured into five phases, emphasizes rigorous evaluation at each stage for effective data-driven decision-making [28]. Inadequate AI training for radiation oncologists and medical physicists poses a challenge for effective AI application in therapy [29]. Predictive digital twins, utilizing Bayesian model calibration, offer a paradigm for personalizing treatment regimens based on patient-specific data [30]. The modular design of cascaded deep networks enhances detection and segmentation accuracy by focusing on specific tasks [31]. These principles and mechanisms underscore a multidisciplinary approach in cancer management, contributing to improved patient outcomes through tailored and precise interventions.

In recent years, the application of Positron Emission Tomography (PET) in cancer management has undergone significant evolution, driven by both technological advancements and the integration of artificial intelligence (AI). As illustrated in Figure 2, the hierarchical structure of PET imaging encompasses various facets that are crucial for understanding its role in clinical practice. This figure highlights the advancements in imaging techniques, such as noise reduction and improved image quality, which have been pivotal in enhancing diagnostic accuracy. Furthermore, the integration of AI and machine learning has led to notable contributions in image enhancement and predictive modeling, thereby augmenting the capabilities of PET imaging. However, the figure also underscores the challenges that persist within technological and data-related domains, reflecting the complexity and ongoing development in this field. This comprehensive overview not only provides a visual representation of the current landscape of PET imaging but also emphasizes the need for continuous innovation and adaptation in cancer management strategies.

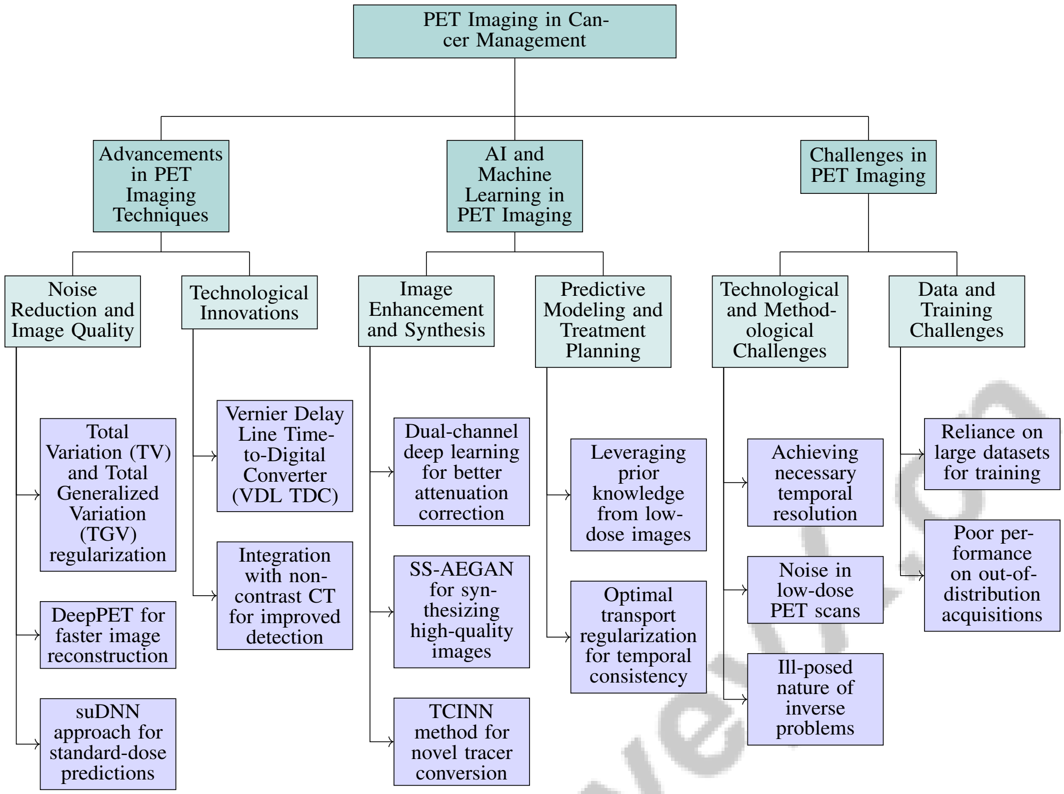

Figure 2: This figure illustrates the hierarchical structure of PET imaging in cancer management, highlighting advancements in imaging techniques, the integration of AI and machine learning, and the challenges faced. The advancements include noise reduction, improved image quality, and technological innovations, while AI contributions focus on image enhancement and predictive modeling. Challenges are identified in technological and data-related areas, emphasizing the complexity and ongoing development in PET imaging.

3 PET Imaging in Cancer Management

3.1 Advancements in PET Imaging Techniques

Recent advancements in PET imaging have significantly enhanced image quality and diagnostic precision, tackling challenges such as noise and low spatial resolution. Techniques like Total Variation (TV) and Total Generalized Variation (TGV) regularization effectively reduce noise while preserving image details, outperforming traditional methods [12]. Integrating AI and machine learning further boosts PET capabilities; DeepPET, for instance, reconstructs images from sinogram data 108 times faster than conventional approaches, improving image quality metrics [6].

The suDNN approach predicts standard-dose images from low-count PET and multi-contrast MRI data, showing resilience to out-of-distribution data and enhancing diagnostic accuracy [7]. Utilizing multiple low-dose PET images with high-resolution ResNet architecture has improved standard-dose predictions [32]. Technologies like the Vernier Delay Line Time-to-Digital Converter (VDL TDC) achieve 25 picoseconds temporal resolution with low power, marking a significant leap over existing designs [33].

PET's application in clinical radiation oncology spans various cancers, including neuro-oncology, head and neck, lung, gastrointestinal, and prostate cancers [34]. Advanced methodologies integrating PET with non-contrast CT have improved detection sensitivity and reduced subjectivity in identifying gross tumor volumes in lymph nodes (GTVLN) [35]. These innovations contribute to precision medicine, enabling more accurate and personalized cancer treatments.

As illustrated in Figure 3, recent advancements in PET imaging techniques are categorized into image enhancement methods, technological innovations, and clinical applications. The first subfigure depicts a linear fit correlating the mean of double and triple image Region of Interest (ROI) activity with activity measured in microcuries per milliliter (uCi/mL), underscoring PET's quantitative capabilities. The second subfigure compares the point spread Full Width at Half Maximum (FWHM) in three-photon PET imaging through Monte Carlo simulations, highlighting improved resolution for both small animal and human scanners. The final subfigure presents a parallel robot system with a PET ring and helmet, designed for precise imaging and enhanced safety, as demonstrated on a mannequin in a controlled environment. These advancements signify the evolution of PET imaging, promising more accurate cancer diagnostics and treatment planning [36, 37, 38]. Through these innovations, PET imaging continues to play a pivotal role in enhancing diagnostic accuracy and treatment planning in clinical oncology.

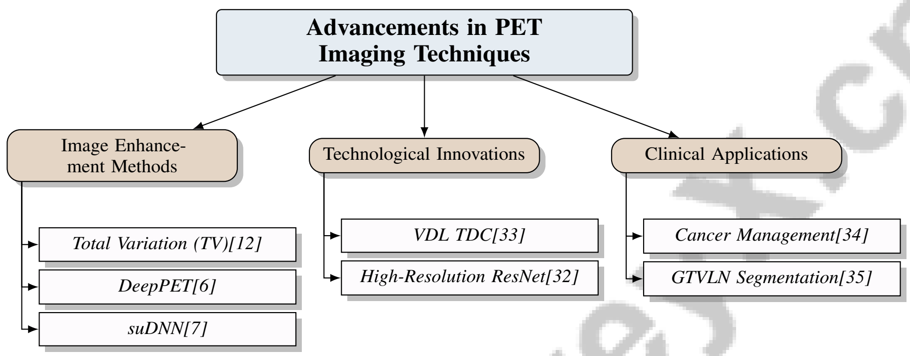

Figure 3: This figure illustrates the recent advancements in PET imaging techniques, categorized into image enhancement methods, technological innovations, and clinical applications. The image enhancement methods include Total Variation (TV), DeepPET, and suDNN, which focus on improving image quality and noise reduction. Technological innovations such as the Vernier Delay Line Time-to-Digital Converter (VDL TDC) and High-Resolution ResNet contribute to improved temporal resolution and image predictions. Clinical applications highlight PET's role in cancer management and GTVLN segmentation, enhancing diagnostic accuracy and treatment planning.

3.2 AI and Machine Learning in PET Imaging

AI and machine learning have significantly improved PET imaging by enhancing diagnostic accuracy and treatment planning, addressing issues like noise reduction and image enhancement. As illustrated in Figure 4, the hierarchical structure of AI and machine learning applications in PET imaging emphasizes three primary categories: image enhancement, image synthesis, and predictive modeling. Each category highlights key methodologies and innovations that contribute to the advancement of PET imaging technologies. Dual-channel deep learning approaches use both PET-nonAC and PET-SegAC images for better attenuation correction and image quality [11]. CNNs and GANs are pivotal in image enhancement, with methodologies categorized into supervised and unsupervised learning [39].

Unsupervised deep learning frameworks have outperformed traditional denoising methods, achieving higher contrast-to-noise ratio (CNR) improvements while preserving image details [40]. The Anatomical Prior Blind Deconvolution (APBD) method enhances the estimation of the point spread function (PSF) and the original PET image by integrating anatomical priors from high-resolution CT images [41]. This integration is crucial for improving image quality and diagnostic precision.

AI-driven innovations like SS-AEGAN, a GAN using self-supervised learning and adaptive residual estimation, synthesize high-quality standard-dose PET images from low-dose inputs, showcasing AI's potential in image synthesis [42]. The TCINN method exemplifies novel tracer conversion, transforming FDG PET images into DOPA PET images without additional tracers, expanding diagnostic capabilities [43].

Leveraging prior knowledge from multiple low-dose PET images has enhanced image quality, reduced noise, and improved signal detection, demonstrating the value of additional data for improved outcomes [32]. Optimal transport regularization addresses dynamic inverse problems by ensuring temporal consistency and reducing kinetic energy in image reconstruction [44].

AI applications extend to predictive modeling and treatment planning, potentially improving patient outcomes in radiation oncology [21]. This survey highlights the challenges and methodologies associated with machine learning algorithms for image analysis, emphasizing AI's transformative role in facilitating precise and personalized cancer management strategies [45].

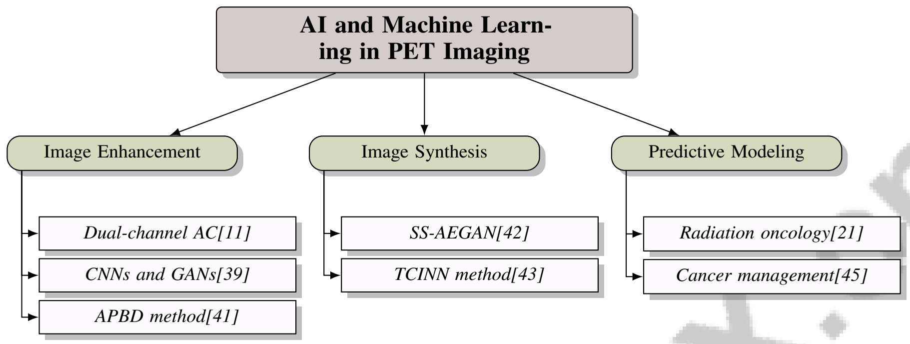

Figure 4: This figure illustrates the hierarchical structure of AI and machine learning applications in PET imaging, focusing on image enhancement, image synthesis, and predictive modeling. Each category highlights key methodologies and innovations that contribute to the advancement of PET imaging technologies.

3.3 Challenges in PET Imaging

PET imaging faces several challenges that impede its clinical efficacy. Achieving the necessary temporal resolution to accurately differentiate gamma ray arrival times at detectors is a notable technological hurdle [33]. Noise in low-dose PET scans, from reduced tracer doses, leads to increased noise levels and decreased signal-to-noise ratio (SNR) [32], complicating high-quality full-dose image synthesis and retention of anatomical details [46].

The ill-posed nature of the inverse problem in PET imaging, where multiple solutions can yield the same observations, is worsened by variability in point spread functions (PSFs) across scanners [41]. Image reconstruction from list-mode data is further complicated by limited events and the inverse problem's ill-posed nature [47]. Additionally, the coupling of SNR with measurement resolution and regularization parameters presents challenges, especially since Poisson noise is not independent of the ground truth [44].

Traditional reconstruction methods, such as filtered back-projection (FBP) and ordered subset expectation maximization (OSEM), often introduce artifacts and noise due to data/model mismatches and inefficiencies in regularization [6]. High scatter levels in imaging modalities like CBCT further compromise image accuracy and reconstruction quality [48].

Methodologically, reliance on large datasets for training neural networks presents a significant challenge. High-quality, diverse datasets accurately reflecting clinical tasks and patient populations are crucial for developing generalizable algorithms [45]. Existing methods often fail to effectively utilize additional information from multiple low-dose PET images, relying solely on a single dose level [32]. This limitation results in poor performance on new out-of-distribution (OOD) acquisitions, as existing deep neural network (DNN) methods primarily focus on training with data closely matching the statistical characteristics of the training data [7].

Furthermore, distinguishing gross tumor volumes in lymph nodes (GTVLN) from surrounding tissues remains challenging due to poor contrast, variability in size and shape, and subtle metastasis signs in non-contrast imaging [35]. Addressing these challenges requires ongoing research and technological advancements, including developing advanced denoising techniques, improved reconstruction algorithms, and robust AI models capable of generalizing across diverse datasets. These efforts are essential for enhancing the efficacy and reliability of PET imaging in precision cancer treatment.

4 Biological Guide Radiotherapy

4.1 Biological Guide Radiotherapy and Precision Dosing

Biological guide radiotherapy represents a paradigm shift in radiation oncology, emphasizing the customization of radiation doses based on biological markers to enhance therapeutic precision and effectiveness. This approach leverages advancements in imaging and genomics, integrating precision medicine tools to enable targeted interventions tailored to the unique biological characteristics of each tumor [49].

A crucial component of biological guide radiotherapy is the ability to monitor and adjust treatments in real-time. Systems like DoPET exemplify this capability by verifying proton range during therapy, closely matching Monte Carlo predictions and thereby improving the precision of proton therapy [50]. This real-time monitoring ensures accurate radiation delivery to the target while minimizing exposure to surrounding healthy tissues.

Innovative imaging techniques further enhance precision dosing. For instance, the generation of synthetic CT images from CBCT data through iterative correction processes improves anatomical coherence and data consistency, which are essential for precise dose calculation and delivery [51]. Additionally, dual-isotope PET imaging methodologies employ data subtraction techniques to isolate images from pure positron emitters, thereby increasing the specificity and clarity of biological markers used for dose guidance [52].

The development of clinically viable radiotracers, such as $^{52g}\mathrm{MnCl}_2$ produced via natV(,x) and natCr(p,x) routes, supports PET imaging in radiotherapy by providing reliable imaging agents compatible with treatment protocols [53]. These advancements in radiotracer production and imaging modalities are critical for the success of biological guide radiotherapy, ensuring that dose adjustments are informed by accurate and timely biological data.

Furthermore, the use of advanced segmentation models, like SAM, enhances precision dosing through improved target delineation, despite variability in performance across different anatomical sites, highlighting the need for continuous refinement [54]. Effective visualization techniques also aid in the interpretability of spatial clustering results, facilitating enhanced patient stratification and informed treatment decision-making [55].

5 Adaptive Radiotherapy

5.1 Real-time Adaptation and Online Adaptive Radiation Therapy (OART)

Method Name	Technological Integration	Adaptation Types	Implementation Challenges
CDDPM[56]	Deep Learning	-	Resource Demands
PMM-ART[57]	Image Processing Techniques	Daily Adaptation	Resource-intensive Nature
RTapp[58]	Predictive Algorithm	Real-time Predictions	Resource Demands
TTO[59]	Deep Learning Models	Online Adaptive Radiotherapy	Computation Time
RgDL[60]	Deep Learning Models	Online Art	Resource Demands
ARTS[61]	Mathematical Modeling	Adaptive Dosing Strategies	Clinical Adoption Challenges
DBG-GTVLN[35]	Deep Learning Framework	Distance-based Gating	Quality OF Input

Table 1: This table presents a comprehensive comparison of various methods employed in real-time adaptation and online adaptive radiation therapy (OART). It details the technological integration, adaptation types, and implementation challenges associated with each method. By highlighting the diversity in approaches and the obstacles faced, it underscores the complexity and potential of OART advancements.

Real-time adaptation and Online Adaptive Radiation Therapy (OART) are transformative in radiation oncology, enabling dynamic modifications to treatment plans based on real-time data, thereby enhancing therapeutic precision and efficacy [62, 63]. The ART framework encompasses offline, online, and real-time adaptations, each addressing treatment variations uniquely [63]. Technological advancements, especially in artificial intelligence (AI), have significantly propelled OART, improving efficiency, accuracy, and overall care quality [64]. Conditional denoising diffusion probabilistic models (DDPM) have been proposed to convert CBCT images into synthetic CT (sCT) images, enhancing image quality for dose calculation and adaptations [56]. Table 1 provides a detailed comparison of methods in real-time adaptation and online adaptive radiation therapy (OART), illustrating their technological integration, adaptation types, and implementation challenges.

Despite these advancements, clinical implementation of OART faces challenges, including the need for rapid image processing and timely plan adjustments within session constraints [65]. The resource-intensive nature of ART demands substantial time and expertise, hindering universal adoption [57]. Offline ART workflows, characterized by extensive manual intervention, can delay adaptations, potentially compromising treatment efficacy [58]. Innovative strategies like Test-Time Optimization (TTO) iteratively adjust pre-trained deep learning model weights during inference to create personalized segmentation models for patients [59]. The registration-guided deep learning (RgDL) framework enhances segmentation accuracy by integrating image registration algorithms with deep learning [60]. Additionally, adaptive radiation treatment strategies (ARTS) employ dynamical system models to optimize radiation dosing schedules tailored to tumor cell interactions [61]. The distance-based gating method enhances real-time adaptation by focusing on specific features of GTVLN categories, integrating clinical reasoning into technological solutions to address OART implementation challenges [35].

5.2 Technological Advancements in Adaptive Radiotherapy

Method Name	Technological Innovations	Adaptive Workflow	Data Integration
PMM-ART[57]	Multivariate Modeling Techniques	Adaptive Radiotherapy Process	Retrospective Imaging Data
CDDPM[56]	Conditional Ddpm Framework	Conditional Denoising Diffusion	Paired Training Data
RgDL[60]	Deep Learning Models	Comprehensive Process	Multimodal Data
IDOL[66]	Mri Super-resolution	Adaptive Radiotherapy	Multimodal Data
TTO[59]	Deep Learning Models	Online Adaptive Radiotherapy	Multimodal Data

Table 2: Summary of recent technological innovations in adaptive radiotherapy, highlighting methods such as PMM-ART, CDDPM, RgDL, IDOL, and TTO. Each method is evaluated based on its technological innovations, adaptive workflow, and data integration capabilities. This table provides a comprehensive overview of how these advancements contribute to the precision and adaptability of treatment plans in adaptive radiotherapy.

Recent innovations in adaptive radiotherapy have significantly improved treatment plan precision and adaptability through advanced imaging techniques, computational models, and data-driven approaches. A comprehensive adaptive workflow incorporating multiple roles facilitates real-time adaptability and improves outcomes in response to dynamic tumor and anatomical changes [62]. The Contour-Guided Deformable Image Registration (CG-DIR) method enhances the accuracy of deformation vector fields by incorporating edited contours, ensuring precise anatomical alignment during adaptive radiotherapy [65]. Despite these advancements, implementing ART workflows in clinical settings remains complex, necessitating further validation across diverse scenarios [57]. Innovative imaging methodologies, such as self-attention cycle generative adversarial networks (cycleGAN), improve the quality of sCT images derived from CBCT, supporting adaptive radiotherapy [56]. A comprehensive evaluation framework incorporating image similarity and clinically relevant dose metrics provides a holistic assessment of synthetic CT generation methods, ensuring adaptive techniques meet clinical standards for image quality and dosimetric accuracy [60]. Table 2 presents a detailed comparison of various methodologies employed in adaptive radiotherapy, emphasizing their technological innovations, adaptive workflows, and data integration strategies.

In predictive modeling, the Ensemble Feature Selection (EFS) model utilizes multi-omics data to predict tumor volume changes in patients undergoing PULSAR treatment for brain metastases [57]. The IDOL framework further enhances deep learning model performance in adaptive radiotherapy by leveraging patient-specific prior information, improving accuracy and reducing adaptation time [66]. Combining image and clinical text data improves target volume delineation accuracy, showcasing the potential of multimodal data integration [59]. Incorporating patient-specific anatomical variations into the segmentation process enhances the relevance of adaptive radiotherapy for individual treatments [60]. These advancements underscore the transformative potential of adaptive radiotherapy, continuously adjusting treatment plans to accommodate dynamic anatomical changes, facilitating personalized and effective radiation therapy. By leveraging real-time imaging feedback, adaptive radiotherapy aims to enhance clinical outcomes and minimize radiation exposure to surrounding healthy tissues, addressing the complexities inherent in cancer treatment [65, 62, 1].

6 Molecular Imaging and Radiation Oncology

6.1 Integration of Molecular Imaging with Radiation Oncology

The integration of molecular imaging with radiation oncology represents a pivotal advancement in cancer treatment, enhancing understanding of tumor biology and improving therapeutic precision. Techniques like positron emission tomography (PET) provide vital insights into tumor metabolic and functional characteristics, aiding accurate treatment planning and monitoring. Advanced time-of-flight PET (TOF-PET) systems, employing resistive plate chamber (RPC) technology, offer higher sensitivity and improved resolution, suitable for both small animal studies and comprehensive whole-body examinations [67].

Recent PET imaging advancements, such as PET-CM techniques, synthesize full-dose PET images from low-dose inputs, maintaining image quality while reducing computation time and patient exposure to radioactive tracers [68]. Multi-threaded approaches powered by graphics processing units (GPUs) further enhance processing speed and image quality, enabling rapid full-body PET image reconstruction [69]. These innovations facilitate the seamless integration of molecular imaging data into radiation oncology workflows, supporting real-time decision-making and adaptive treatment strategies.

The synergy between molecular imaging and radiation oncology is bolstered by the capability to visualize and quantify biological processes at the cellular level, offering insights into tumor heterogeneity and treatment response. This integration enhances target delineation accuracy and dose delivery, allowing for personalized treatment regimens that account for the unique biological characteristics of each patient's cancer. As molecular imaging technologies evolve, their integration into radiation oncology is poised to refine treatment protocols, enabling precise tumor delineation and individualized cancer management strategies. Techniques such as image-guided radiotherapy, intensity-modulated radiotherapy, and PET are transforming the radiotherapy landscape by identifying tumor heterogeneity and radio-resistance areas, facilitating tailored radiation dosing and improved therapeutic response monitoring, ultimately leading to better patient outcomes and reduced long-term radiation therapy toxicities [2, 1, 34].

6.2 Molecular Imaging Innovations

Innovations in molecular imaging have significantly advanced cancer diagnosis and treatment, primarily through artificial intelligence (AI) integration, which enhances segmentation accuracy and efficiency, reducing clinician workload and improving treatment outcomes [70]. AI-driven segmentation models enable precise tumor boundary delineation, crucial for accurate treatment planning and monitoring.

Emerging modalities, such as granzyme B PET imaging, serve as predictive biomarkers for immunotherapy response, facilitating earlier and more precise treatment decisions [22]. This capability is essential in personalized medicine, which tailors treatment to individual patient characteristics.

Innovative techniques like IH-XPCT, combining X-ray phase contrast tomography with immunohistochemistry, provide unique visualizations of specific cells in their biological context, enhancing understanding of tumor biology and cellular processes [23]. This integration of imaging modalities addresses tumor heterogeneity, a key factor in developing effective treatment strategies.

The advent of predictive digital twins, using Bayesian model calibration, marks a paradigm shift in personalizing treatment regimens based on patient-specific data [30]. These digital models simulate patient responses to various treatment scenarios, optimizing therapeutic interventions and improving patient outcomes.

The ongoing evolution of molecular imaging technologies is expected to further enhance cancer treatment precision and personalization. Future directions include refining AI algorithms for higher segmentation accuracy, developing novel imaging biomarkers for better treatment response assessment, and integrating multimodal imaging data—such as radiology images, histopathology slides, and clinical information—to create a comprehensive understanding of tumor biology. This integration aims to leverage multimodal approaches, including late fusion techniques and large language models, which show promise in improving predictive accuracy and generalization across diverse patient populations and clinical settings, thereby facilitating more effective and personalized cancer treatment

AI-generated, for reference only.

strategies [70, 71, 72, 73]. These innovations hold the potential to transform cancer management, offering more effective and tailored therapeutic strategies for improved patient care.

7 Personalized Cancer Treatment

7.1 Personalized Cancer Treatment Approaches

Personalized cancer treatment marks a significant evolution in oncology, emphasizing the customization of therapeutic strategies to individual patient profiles, thereby improving treatment efficacy and outcomes. This approach utilizes advanced technologies such as PET imaging, biological guided radiotherapy, adaptive radiotherapy, and molecular imaging to tailor interventions based on each patient's unique biological and clinical characteristics. These innovations enhance tumor delineation, allow for real-time treatment adjustments, and identify radio-resistant tumor regions, aiming to improve clinical outcomes while reducing radiation-related side effects [49, 1, 3, 74].

The integration of PET/CT imaging with automated lesion segmentation, augmented by data augmentation and multitask learning, significantly improves the accuracy and efficiency of tumor detection and delineation [27]. This is crucial for developing personalized treatment plans that precisely target tumor sites while sparing healthy tissues.

AI models like the Mixture of Multicenter Experts (MoME) demonstrate the potential of combining expertise from various centers to create adaptive systems capable of generalizing across diverse clinical settings [73]. These models support the personalization of treatment strategies by integrating extensive clinical data and adapting to individual patient needs.

Incorporating patient preferences and clinician expertise into therapeutic decision-making is advanced by methods like Adaptive Weight Learning for Multiple Outcome Optimization (AWL-MOO), which optimizes composite outcomes with continuous treatments while considering unknown utility functions [75]. This ensures that treatment plans are biologically tailored and aligned with the values of patients and healthcare providers.

The shift from empirical dosing to evidence-based, personalized radiotherapy underscores the importance of considering individual tumor biology in treatment planning [49]. Innovations such as biodegradable mesoporous silica nanoparticles (bMSNs) for delivering neoantigens and adjuvants enable personalized cancer vaccination and photodynamic therapy (PDT) [76], enhancing treatment specificity and effectiveness through targeted delivery.

The integration of advanced technologies and methodologies, including machine learning, natural language processing, and genomic analysis, highlights the transformative potential of personalized cancer treatment. It facilitates accurate diagnostics, tailored therapeutic interventions, and continuous optimization of treatment plans based on individual patient data and dynamic disease states [21, 49, 3, 77]. By incorporating advanced imaging, AI-driven models, and patient-centered approaches, oncology is advancing towards more precise and effective therapeutic strategies, ultimately improving patient outcomes and quality of life.

7.2 AI and Data-Driven Approaches in Treatment Customization

AI and data-driven methodologies are transforming personalized cancer treatment by enabling the customization of therapeutic strategies through comprehensive data analysis and model-driven insights. The Mixture of Multicenter Experts (MoME) framework exemplifies this transformation, integrating multiple expert systems tailored to specific clinical environments, thereby enhancing AI model performance and adaptability to diverse practices [73]. This framework ensures that treatment strategies are precisely aligned with individual patient needs.

In target volume contouring, the development of LLMSeg represents a significant advancement, utilizing large language models (LLMs) to condition segmentation models with clinical information, thus improving the accuracy and precision of target volume delineation [72]. By merging clinical data with advanced AI techniques, LLMSeg enhances healthcare professionals' ability to accurately define treatment areas, crucial for effective radiation therapy planning.

The integration of AI in treatment customization significantly optimizes therapeutic regimens by employing advanced models that meticulously analyze patient-specific data. These models identify optimal treatment pathways and facilitate a precise and efficient approach to personalized medicine, particularly in complex fields like radiation oncology. By transforming unstructured clinical data from electronic health records into structured information, AI recognizes intricate patterns, improving the accuracy and quality of cancer therapies while addressing the increasing complexity of treatment protocols and resource scarcity in healthcare settings [64, 77]. These models incorporate a broad spectrum of clinical variables, including genetic, environmental, and physiological factors, to tailor interventions that maximize efficacy while minimizing adverse effects.

The integration of AI and data science in cancer treatment enhances precision medicine by identifying complex patterns in patient data, optimizing therapeutic interventions, and facilitating continuous disease monitoring through advanced biomarker discovery and analysis of extensive clinical datasets. This approach not only improves diagnostic accuracy and treatment efficacy but also addresses the multifaceted challenges of individualized patient care in oncology [64, 3, 77, 78]. By harnessing AI's capabilities to analyze complex datasets and model patient-specific interactions, healthcare providers can develop more effective and individualized treatment strategies, ultimately enhancing patient outcomes and quality of care.

8 Challenges and Future Directions

8.1 Challenges and Solutions

Integrating advanced technologies in cancer treatment presents challenges that require strategic solutions and further research to optimize therapeutic outcomes. PET imaging's reliance on 2D convolution limits comprehensive axial data extraction; adopting 3D convolution could address this by capturing more spatial features, though low-dose image information loss remains a challenge [7]. The use of synthetic data in AI model training, as demonstrated in the DeepPET study, may impede generalizability due to real patient data complexities [6]. Future research should improve forward models to incorporate 3D imaging and Poisson noise statistics, with robust priors for point spread function estimation [41].

Variability in manual annotations and achieving generalizability across clinical settings can hinder AI-driven segmentation models. Developing robust AI models that generalize across diverse environments, supported by high-quality labeled data, is essential [79]. The SAM model, while effective, struggles with smaller organs and indistinct boundaries, indicating current limitations [54]. The reliance on specific datasets poses challenges, as parameter-efficient fine-tuning may falter with limited data or different scanner types. Expanding training datasets to include a broader range of scanner types and clinical scenarios is crucial for enhancing model robustness and adaptability [80].

In radiation therapy, variations in the position and shape of organs-at-risk (OARs) relative to the pancreas can lead to excessive doses, highlighting the need for improved imaging and treatment planning techniques [35]. Future research should focus on optimizing computational efficiency without sacrificing accuracy, possibly through advanced algorithms and high-performance computing resources [68]. The reliance on robust network infrastructure for post-radiotherapy PET image outcome prediction necessitates exploring decentralized and resource-efficient models suitable for diverse clinical environments [79].

The complexity of neural networks in cancer treatment poses computational resource demands and overfitting risks. Addressing these issues requires optimizing network architectures and employing techniques like cross-validation and regularization to ensure model generalizability and robustness [66]. The reliance on diverse low-dose PET images for training may limit clinical applicability. Future research should explore methods to synthesize or simulate varying dose-level images, broadening the applicability of advanced imaging techniques [32].

Enhancing quantum efficiency and optimizing the RPC TOF-PET system for various medical applications could yield new diagnostic tools [33]. Fine-tuning GPT-RadPlan based on clinician feedback and exploring its application in proton therapy could enhance its utility in automated radiotherapy treatment planning [5]. Despite its advantages, Test-Time Optimization (TTO) may face challenges related to computation time, particularly when initiated from a randomized model instead of a pre-trained one [59].

A multidisciplinary approach is vital to effectively address these complex challenges. This approach should focus on developing sophisticated computational techniques, enhancing training datasets through diverse data sources, and establishing standardized clinical protocols to ensure consistency and reliability in clinical applications. Such strategies are critical for leveraging advanced technologies like Natural Language Processing (NLP) and artificial intelligence in personalized and precision medicine, ultimately aiming to improve diagnostic accuracy and treatment efficacy [3, 77]. Concentrating on these areas can significantly enhance the precision and efficacy of cancer treatment, leading to improved patient outcomes.

8.2 Future Directions and Research Opportunities

Future research in cancer treatment aims to leverage advancements in imaging, AI, and personalized medicine to enhance therapeutic efficacy and precision. The scalability of the Explainable Spatial Clustering approach across diverse cancer types, paired with refined visualizations for broader clinical scenarios, offers promising opportunities for improving patient stratification and treatment planning. Research in synthetic CT generation, such as IVNAC, highlights the potential for rapid, accurate imaging with reduced radiation exposure, benefiting clinical workflows [81]. Efforts to refine imaging techniques through content loss functions, patch-level synthesis, and SGSGAN applications to modalities like CT and MRI demonstrate a commitment to enhancing clinical applications [46].

In PET imaging, validating DeepPET with real clinical data and exploring its applicability to other imaging modalities, such as SPECT and CT, should be a focus of future research [6]. Developing predictive models validated across larger, diverse patient populations will further enhance personalized treatment strategies [57]. Investigating complex network architectures and evaluating methods across varied clinical datasets will address registration errors and improve multimodal imaging data integration. Non-rigid registration techniques and performance evaluations across different imaging scenarios and doses are critical for refining adaptive radiotherapy methods [48].

Exploring new PET tracers, radiomics, and deep learning techniques to enhance tumor characterization and treatment strategies remains a priority [34]. Standardizing evaluation metrics, utilizing larger and more diverse datasets, and investigating the clinical implementation of DL-based synthetic CT across various anatomical sites are essential for advancing these technologies [82]. Extending framework adaptability to systems lacking DICOM Q/R capabilities will enhance utility in diverse clinical settings [83].

Extending frameworks to 3D images, enhancing uncertainty maps, and evaluating methods on larger datasets will improve the robustness and applicability of imaging techniques [7]. Enhancing algorithms to infer context from minimal data and exploring real-time applications will advance radiobiology and treatment planning systems. These research opportunities underscore the potential for significant advancements in cancer treatment, driven by innovations in imaging, AI, and personalized medicine, ultimately aiming to improve patient outcomes and quality of life.

9 Conclusion

The integration of cutting-edge imaging technologies, biological insights, and personalized therapeutic approaches is central to advancing modern cancer management. This multidimensional strategy not only improves diagnostic precision but also enhances therapeutic outcomes. PET imaging, exemplified by ^{68}Ga-PSMA-11 PET/CT, plays a critical role in detecting recurrent prostate cancer, thereby refining treatment planning and execution. The incorporation of AI and machine learning within radiation oncology further boosts precision and efficiency, easing the operational burden on healthcare professionals and enabling more effective clinical interventions.

Personalized treatment strategies, underpinned by comprehensive genomic profiling, have shown to significantly improve disease control and survival rates. Innovative methodologies, such as the predictive digital twin, offer promising avenues for optimizing radiation doses and extending progression-free survival. Moreover, precision dosing strategies, informed by tumor hypoxia imaging, demonstrate the potential to minimize toxicity while maximizing therapeutic efficacy.

The adoption of these enabling technologies highlights their transformative potential in tailoring treatments to individual patient characteristics, thereby improving outcomes. As the field progresses, training in AI becomes indispensable for practitioners to fully harness these advancements. Addressing challenges such as noise through structured decision-making and technology integration can further enhance clinical outcomes. The application of a comprehensive, data-driven approach, as evidenced in non-small cell lung cancer treatment, underscores the importance of integrating diverse data sources to refine clinical predictions. Collectively, these multidisciplinary approaches promise substantial improvements in patient care, emphasizing the need for continued innovation and collaboration in oncology.

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