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Clinical Anatomy in Imaging: Leveraging Structural Data for Enhanced Pathological Precision

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Abstract

The integration of clinical anatomy with advanced imaging technologies is essential for enhancing diagnostic precision, yet a comprehensive synthesis of current methodologies and their clinical applications remains lacking. This review addresses the growing need for standardized approaches to leverage structural data in pathology, particularly as imaging and artificial intelligence (AI) evolve rapidly. Bridging anatomical knowledge with technological advancements is critical to improving patient-specific diagnostics and treatment planning. This review highlights how 3D modeling and AI-driven analysis refine surgical navigation and tumor detection, while radiomics enables non-invasive prediction of genetic mutations in diseases like lung adenocarcinoma. We discuss the role of multimodal imaging in capturing complex anatomical-pathological relationships and the transformative potential of deep learning in automating segmentation and diagnosis. Key insights include the synergy between anatomical expertise and machine learning for early disease detection, as well as challenges in data standardization and model interpretability. Emerging tools, such as neural radiance fields and digital biobanks, are also examined for their capacity to unify imaging with multi-omics data. Future research must prioritize multicenter collaborations to validate AI models across diverse populations and imaging protocols. Innovations in real-time imaging analytics and explainable AI will be pivotal for clinical adoption. Ultimately, this integration promises to advance precision medicine, offering tailored therapeutic strategies grounded in robust anatomical and pathological insights.

Keywords: Artificial intelligence, Clinical anatomy, Medical imaging, Pathological precision, Radiomics, Structural data, Three-dimensional modeling, Precision medicine

Introduction

Medical imaging plays a crucial role in modern medicine, providing visual representations of the body's interior for clinical analysis, medical intervention, and establishing baselines for detecting subtle abnormalities [1-4]. The field is constantly evolving, driven by advancements in technology and a growing need for more precise and personalized approaches to healthcare [5-7]. One of the most promising avenues for improvement lies in leveraging structural data from clinical anatomy within medical imaging to enhance pathological precision, ultimately leading to better diagnoses, treatment planning, and patient outcomes [8-11]. This article will explore how integrating anatomical knowledge with advanced imaging techniques can lead to a more comprehensive understanding of disease processes.

The integration of clinical anatomy with advanced imaging techniques is pivotal for enhancing pathological precision in medical diagnostics and treatment planning [12-14]. Recent literature highlights various methodologies and technologies that leverage structural data to improve clinical outcomes across different medical fields. One significant advancement is the use of three-dimensional (3D) models derived from imaging data, which has been shown to enhance surgical navigation and preoperative planning. For instance, Liawrungrueang et al. [15] developed high-resolution 3D models of the C1 and C2 vertebrae, enabling comprehensive morphometric analysis that aids in identifying gender differences and assessing bilateral symmetry, ultimately enhancing surgical accuracy. Similarly, Miyoshi [16] emphasizes the construction of 3D models from preoperative imaging data to support surgical simulations and navigation, showcasing the potential of these models in perioperative care.

AI plays a crucial role in refining diagnostic imaging processes. Luvhengo et al. [17] discuss how AI-driven precision oncology can significantly improve the diagnostic workup and management of medullary thyroid carcinoma by processing complex data efficiently. This integration of AI not only enhances diagnostic accuracy but also facilitates risk stratification and follow-up care. Furthermore, Mahmood et al. [18] propose a framework that combines dense convolutional networks with attention mechanisms for breast tissue prognosis, demonstrating the capability of

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AI to enable rapid and precise clinical assessments. In the realm of image segmentation, Abdel-Salam et al. [19] introduces an adaptive enhanced human memory algorithm for multi-level image segmentation of pathological lung cancer images. This algorithm's simplicity and versatility allow for effective segmentation, which is critical for accurate diagnosis and treatment planning. Additionally, Zhang et al. [20] present SpineMamba, a novel framework that enhances 3D spinal segmentation by incorporating residual visual Mamba layers, addressing the limitations of traditional convolutional neural networks in capturing long-range dependencies.

The application of radiomics in predicting genetic mutations further exemplifies the intersection of imaging and clinical anatomy. Deng et al. [21] developed a non-invasive radiomics model based on positron emission tomography (PET)/computed tomography (CT) imaging to predict epidermal growth factor receptor mutations in lung adenocarcinoma, highlighting the potential of imaging data to inform treatment decisions. Moreover, the integration of imaging with genetic data is explored by Paudel et al. [22], who examines cardiac magnetic resonance imaging (MRI) as a gold standard for evaluating cardiomyopathies. This approach enhances early detection and prognostication by revealing subtle structural and functional changes throughout the disease course.

In summary, the literature underscores the transformative impact of integrating clinical anatomy with advanced imaging techniques and AI. These innovations not only enhance diagnostic precision but also improve surgical outcomes and patient management across various medical disciplines [23-25]. The ongoing research in this area promises to further refine the capabilities of imaging technologies, ultimately leading to better patient care.

The Importance of Clinical Anatomy in Imaging

Clinical anatomy plays a crucial role in enhancing the effectiveness of various imaging modalities, thereby improving diagnostic accuracy and patient outcomes across multiple medical fields [26-28]. The integration of anatomical knowledge with advanced imaging techniques is essential for clinicians to accurately interpret images and make informed decisions regarding patient care [29-31]. Recent advancements in imaging technologies, such as micro-CT and cone beam CT, have significantly improved the visualization of anatomical structures in dentistry and maxillofacial surgery [32, 33]. Kamburoğlu [34] highlights that these imaging modalities provide high-resolution, 3D images that are critical for procedures like implantology and endodontics, emphasizing the necessity of a solid understanding of clinical anatomy in these contexts. In the realm of neurology, Pidvalna et al. [35] demonstrate the importance of integrating radiological imaging techniques into anatomy education. Their study illustrates brain anatomy using CT and MRI, which not only aids in the training of young doctors but also serves as a refresher for experienced radiologists. This approach underscores the need for continuous education in clinical anatomy to enhance the interpretation of imaging results.

The significance of anatomical knowledge extends to the evaluation of specific pathologies, as shown by Saran et al. [36], who reviewed the anatomy of the spiral groove and its associated imaging characteristics. Their findings indicate that understanding the anatomical context is vital for selecting appropriate imaging modalities and accurately diagnosing conditions affecting this area. Moreover, Li et al. [37] presents a model that combines radiomics and anatomical features to improve the recognition of symptomatic nerves in primary trigeminal neuralgia. This study exemplifies how a detailed understanding of anatomy can enhance the application of machine learning in imaging, leading to better differentiation between symptomatic and asymptomatic conditions. In the field of urology, Côrtes et al. [38] conducted a scoping review that synthesized evidence on upper urinary tract anatomy through various imaging techniques. Their work highlights the clinical correlations that arise from a thorough understanding of anatomy, which is essential for interpreting imaging results and guiding clinical decisions.

The role of imaging in understanding complex anatomical structures is further emphasized in the context of vascular imaging. Zhang et al. [39] discuss how advancements in nanotechnology have improved the resolution of imaging techniques, allowing for better visualization of microvascular systems. This advancement necessitates a comprehensive understanding of vascular anatomy to fully leverage these technological improvements. In surgical contexts, Nair et al. [40] address the importance of applied anatomy in diagnosing biliary complications following surgical procedures. Their review illustrates how imaging plays a critical role in managing these complications, reinforcing the need for radiologists to possess a strong foundation in clinical anatomy.

Overall, the literature underscores that a robust understanding of clinical anatomy is indispensable for the effective use of imaging techniques across various medical disciplines. As imaging technologies continue to evolve, the integration of anatomical knowledge will remain a cornerstone of accurate diagnosis and effective patient management [41-43].

Advancements in Imaging Technologies

The field of medical imaging encompasses a wide range of technologies, each with its strengths and limitations (Table 1). These include: (i) X-ray radiography: A traditional imaging technique that uses X-rays to visualize bones and dense tissues, (ii) MRI: Provides detailed images of soft tissues, including the brain, spinal cord, and internal organs [44-46], (iii) Medical ultrasonography (Ultrasound): Uses sound waves to create real-time images of organs and tissues, particularly useful for visualizing blood flow and guiding procedures [45, 47], (iv) CT: Combines X-ray images from different angles to create cross-sectional views of the body [15, 20, 48], (v) PET: A functional imaging technique that uses radioactive tracers to detect metabolic activity in the body [44], (vi) Optical coherence tomography (OCT): High-resolution imaging technique used to visualize tissue microstructure, particularly in the eye [49, 50], and (vii) Near-infrared II (NIR-II) imaging: Novel strategies utilizing light in the second NIR region (900 - 1,880 nm wavelengths) offer the potential to visualize and treat solid tumors with enhanced precision [51]. Recent innovations in these technologies, such as improved resolution, faster acquisition times, and enhanced contrast agents, have further improved the visualization of anatomical structures and pathological processes [52-54].

Leveraging Structural Data for Enhanced Pathological Precision

The integration of structural data in pathology has emerged as a pivotal area of research, particularly in enhancing diagnostic precision and

Table 1: Advanced imaging modalities and their clinical applications.

Imaging technology	Key features	Strengths	Limitations	Clinical applications	Future potential
CT	Cross-sectional X-ray imaging	High spatial resolution; fast acquisition	Ionizing radiation; poor soft tissue contrast	Trauma, oncology, spinal assessment	Low-dose protocols; AI-enhanced analysis
MRI	Multi-parametric soft tissue imaging	Excellent contrast; functional data	Expensive; long scan times	Neurodegenerative diseases, musculoskeletal	Ultra-high-field MRI (7T+)
PET	Metabolic imaging with radiotracers	Detects molecular activity	Radiation exposure; limited resolution	Oncology, neurology, cardiology	Novel tracers (e.g., tau-PET)
Ultrasound	Real-time imaging using sound waves	Portable; no radiation	Operator-dependent; limited depth	Obstetrics, intraoperative guidance	AI-assisted automated scanning
OCT	Micron-scale cross-sectional imaging	Very high resolution; non-invasive	Limited penetration depth	Ophthalmology, dermatology, cardiology	OCT angiography advancements
NIR-II	Deep-tissue optical imaging	High resolution; minimal scattering	Emerging technology; limited clinical adoption	Cancer imaging, vascular surgery	Theranostic applications

treatment strategies [55-57]. Recent studies highlight various methodologies and technologies that leverage structural data to improve pathological outcomes. One significant advancement is the use of multimodal imaging data, as demonstrated by Cao et al. [58], who focused on enhancing group-wise consistency in anatomical structures through 3D hinge gyrus matching. Their approach utilized T1 MRI and diffusion tensor imaging to establish precise one-to-one correspondences for anatomical features, which is crucial for accurate pathological assessments. In the realm of cancer diagnostics, Mir et al. [59] introduced a neural network-based method for detecting and isolating brain tumors in MRI images. Their study emphasized a structured approach that significantly improved precision and accuracy in tumor identification, showcasing the potential of advanced imaging techniques in pathology.

Furthermore, the work by Li et al. [60] on a novel cross-shaped windows transformer model for detecting clinically significant prostate cancer illustrates the application of structural data in enhancing diagnostic capabilities. They multitask self-supervised learning framework effectively utilized unlabeled data, thereby improving the model's generalizability and performance in identifying prostate cancer [60]. The challenges associated with generating pathology reports from whole slide images were addressed by Hu et al. [61], who proposed a method that combines knowledge retrieval with multi-level regional feature selection. This approach aims to navigate the structural complexity and high information density of whole slide images, ultimately facilitating more accurate and informative pathology reporting [61]. Moreover, the integration of structural data with genetic information in cardiac imaging, as explored by Paudel et al. [22], underscores the potential for enhanced early detection and treatment strategies for cardiomyopathies. Their findings suggest that combining cardiac MRI with genetic data can reveal underlying inflammatory components, which may inform therapeutic approaches [22].

Several studies demonstrate the benefits of leveraging structural data for enhanced pathological precision. Karagodin et al. [47] showed that a novel 3D echocardiographic tissue transparency tool significantly improved the delineation of cardiac anatomy and pathology. The addition of transparency to transillumination rendering enhanced the ability to recognize anatomy, identify pathology, improve depth perception, and improve border delineation [47]. Chen et al. [45] proposed an anatomy-preserving generative adversarial network to generate simulated intraoperative ultrasound (iUS) images of the liver with precise structural information from preoperative MRI. This allows doctors to understand the characteristics of iUS in advance and expands the iUS dataset for automatic analysis [45]. Zhang et al. [20] developed SpineMamba, a novel framework that incorporates a residual visual Mamba layer and a spinal shape prior module to enhance the structural semantic understanding of vertebrae in 3D clinical images. This approach significantly improves the accuracy of spinal segmentation, which is critical for diagnosing and treating spinal diseases [20]. Pan et al. [46] demonstrated that MRI imagomics, particularly diffusion-weighted imaging and combined T1-weighted imaging/contrast-enhanced T1-weighted imaging with fat saturation (T1WI/CE-T1WI fs) models, significantly enhances gastrointestinal stromal tumor risk stratification. This supports precise preoperative patient assessment and personalized treatment plans [46]. Liawrungrueang et al. [15] developed high-resolution 3D models of the C1 and C2 vertebrae using CT scans to perform comprehensive morphometric analysis. This can enhance surgical precision and reduce intraoperative risks in cervical spine surgeries [15]. A study by Jaus et al. [62] based on anatomy-pathology exchange model exemplifies the integration of anatomical and pathological data to enhance segmentation accuracy. By using a query-based segmentation transformer, anatomy-pathology exchange model decodes a joint feature space into query-representations for human anatomy, which are then interleaved into the pathology-decoder. This method has shown improved results in FDG-PET-CT and chest X-ray pathology segmentation tasks, outperforming baseline methods up to 3.3% [62].

A study by Leon et al. [63] developed a novel method to analyze structural brain MRI images, focusing on identifying anatomical regions that may indicate pathological conditions, particularly Alzheimer's disease. The method involved extracting visual features from brain MRI scans, which were then grouped based on their similarities. This group aimed to highlight regions that share common characteristics, potentially revealing underlying anatomical structures related to Alzheimer's disease. The researchers utilized a probabilistic latent semantic analysis approach to cluster these visual features. This technique allowed them to create a co-occurrence matrix that represented how often certain visual features appeared together in specific regions of the brain. The results indicated that there were significant differences in the visual features between healthy control subjects and those with probable Alzheimer's disease. The differences were more pronounced when comparing healthy subjects to those with advanced Alzheimer's disease, suggesting that the method could effectively distinguish between varying stages of the disease. The analysis showed that certain localized brain regions were particularly relevant for characterizing the stages of Alzheimer's disease. This finding implies that the method could help identify specific areas of the brain that degenerate most during the progression of Alzheimer's disease. The study also highlighted that the differences in visual features could be detected even in the early stages of the disease, which is crucial for timely diagnosis and intervention. This early detection could potentially allow for lifestyle changes that might slow the progression of Alzheimer's disease. Overall, the proposed method not only aids in understanding the morphological abnormalities associated with Alzheimer's disease but also sets the groundwork for future research aimed at quantifying these changes and improving diagnostic techniques [63].

Another study by Khandelwal et al. [64] presents several significant findings regarding the use of high-resolution postmortem MRI in understanding neurodegenerative diseases, particularly Alzheimer's disease. The researchers developed a deep learning-based framework that successfully automates the segmentation of various brain structures, including the cortical mantle, subcortical structures (caudate, putamen, globus pallidus, thalamus), white matter hyperintensities (WMH), and normal appearing white matter. This was validated on 135 postmortem human brain tissue specimens imaged at 7T. The study found significant associations between localized cortical thickness and neuropathological ratings. Specifically, negative correlations were observed between phosphorylated tau (p-tau) levels and cortical thickness in regions such as the angular gyrus and midfrontal areas. This suggests that tau pathology is linked to cortical atrophy and cognitive decline in Alzheimer's disease. There were significant negative correlations between cortical thickness and neuronal loss in Brodmann area 35 and the entorhinal cortex. Additionally, correlations with Braak staging were noted in the midfrontal region, entorhinal cortex, and Brodmann area 35, indicating that these areas are affected by high p-tau uptake as seen in PET imaging. The study reported that high volumes of WMH disrupt structural and functional connectivity, which negatively impacts memory. Significant negative correlations were found between WMH volume and cortical thickness in the posterior cingulate and superior temporal regions. The automated segmentation framework demonstrated generalization capabilities across unseen images acquired with different parameters, indicating its robustness and potential for broader application in neuroimaging studies. In conclusion, the study highlights the effectiveness of automated postmortem MRI analysis in linking brain structure with pathology, providing valuable insights into the mechanisms underlying neurodegenerative diseases like Alzheimer's disease [64].

A study by Wasserthal et al. [65] presented in the paper "TotalSegmentator: robust segmentation of 104 anatomical structures in CT images" yielded several significant results regarding the performance of the deep learning segmentation model. The nnU-Net segmentation algorithm achieved a high Dice similarity coefficient of 0.943 on the test set. This score indicates a strong ability to accurately segment anatomical structures in CT images, which is crucial for various medical applications. The proposed model significantly outperformed another publicly available segmentation model, which achieved a Dice score of 0.871. This comparison highlights the robustness and effectiveness of the TotalSegmentator model in segmenting anatomical structures. The model was trained on a diverse dataset comprising 1204 CT examinations collected from routine clinical studies. This dataset included a variety of factors such as different ages, pathologies, scanners, body parts, sequences, and sites, making it representative of real-world clinical scenarios. The model was also applied to a second dataset of 4004 whole-body CT examinations to investigate age-dependent changes in volume and attenuation of various anatomical structures. The study found significant correlations between age and both volume and mean attenuation for several organ groups, such as the aortic volume and the mean attenuation of the dorsal musculature. These results demonstrate the effectiveness of the TotalSegmentator model in accurately segmenting a wide range of anatomical structures, which can be beneficial for applications in organ volumetry, disease characterization, and surgical or radiotherapy planning [65].

A study by Keene [66] presented several significant findings regarding the methodology and outcomes of neuropathological analyses in Alzheimer's disease. The research included a total of 84 brain samples from donors, with approximately 60% being female. The participants ranged from individuals with no cognitive impairment to those with dementia, providing a broad spectrum of Alzheimer's disease neuropathological changes (ADNC). The study reported high tissue quality metrics, including RNA integrity number, pH, and post-mortem interval. These metrics are crucial for ensuring the reliability of molecular analyses. The nuclear yields for single-cell omics were robust, indicating that the tissue samples were well-preserved and suitable for detailed analysis. The research utilized advanced techniques such as spatial transcriptomics, which performed well with minimal tissue freezing artifacts. This suggests that the modernized methodology effectively preserved the integrity of the samples for molecular studies. Traditional neuropathological examinations confirmed a range of ADNC among the samples. Some donors exhibited additional age-related comorbid pathologies, highlighting the complexity of Alzheimer's disease and its interactions with other conditions. The study employed HALO-based analysis of digital pathology to assess various markers, including beta-amyloid, p-tau, and neuroinflammatory markers. This analysis resulted in a variety of quantitative variables that were used to generate continuous pseudo-progression scores for the cohort, which can inform future molecular omics analyses. The development and implementation of improved methods for tissue collection, characterization, and preservation, combined with enhanced sampling and integrated neuropathology, resulted in a robust resource for supporting modern molecular analyses. This advancement is expected to significantly contribute to understanding the cellular and molecular mechanisms underlying Alzheimer's disease. These results underscore the importance of modernized methodologies in enhancing the quality and applicability of neuropathological research in Alzheimer's disease [66].

Overall, the literature indicates a growing recognition of the importance of leveraging structural data in pathology. The advancements in imaging technologies, machine learning models, and integrative approaches highlight a transformative shift towards more precise and effective diagnostic and therapeutic strategies in the field.

AI and Radiomics

The integration of AI and radiomics has revolutionized medical imaging, enhancing diagnostic precision and personalization in medical treatments [16, 17, 48]. AI algorithms can analyze vast amounts of imaging data, identify subtle patterns, and provide quantitative assessments that may not be apparent to the human eye [17, 18]. Radiomics involves extracting quantitative features from medical images to create a comprehensive view of disease biology [48]. These features can be used to predict treatment response, assess prognosis, and personalize treatment plans [46]. Deep learning models, particularly convolutional neural networks, have shown remarkable success in medical image analysis [18, 50, 67]. They can automatically learn complex patterns from images and improve diagnostic accuracy in various applications, including tumor detection, segmentation, and classification [18, 20, 50, 68]. A study by Lau et al. [69] proposed dual-acquisition 3D super-resolution method enhances ultra-low-field MRI for high-quality brain imaging by leveraging deep learning trained on high-field brain data (Figure 1). This approach has the potential to make ultra-low-field MRI a viable, cost-effective solution for brain imaging, particularly in point-of-care settings and in low- and middle-income countries [69]. The combination of AI and radiomics with anatomical knowledge can lead to more accurate and reliable diagnostic tools (Table 2).

A study by Shimada et al. [70] included a total of 720 patients with clinical stage 0-IA non-small cell lung cancer (NSCLC) who underwent complete surgical resection. These patients were divided into two groups: a derivation cohort of 480 patients and a validation cohort of 240 patients. In the derivation cohort, 12% of patients (56 individuals) had positive lymph nodes, while in the validation cohort, 11% (27 individuals) had positive lymph nodes. This indicates a similar prevalence of lymph node metastasis across both groups. The researchers found that the status of pathological lymph nodes significantly affected overall survival and recurrence-free survival. For instance, in the derivation cohort, the 5-year overall survival rate was 92.4% for patients without pathological lymph nodes compared to 63.8% for those with pathological lymph nodes. Similarly, the 5-year recurrence-free survival rate was 84.5% versus 40.1% for the same groups, respectively. The study identified several factors associated with pathological lymph nodes. Notably, the average solid CT value and solid-part size of tumors were independently linked to pathological lymph nodes status. The average solid CT value had an area under the curve of 0.761, with a cut-off value of -103 Hounsfield units being significant for predicting pathological lymph nodes. The analysis also revealed that larger solid-part sizes were associated with a higher risk of pathological lymph nodes. For example, a solid-part size greater than 1.83 cm showed a pathological lymph nodes ratio of 23% compared to 4% for smaller sizes in the derivation cohort. The study concluded that using AI software for CT-based radiomics can effectively predict pathological lymph nodes in patients with early-stage NSCLC. This predictive capability may help guide surgical decisions and postoperative treatments [70].

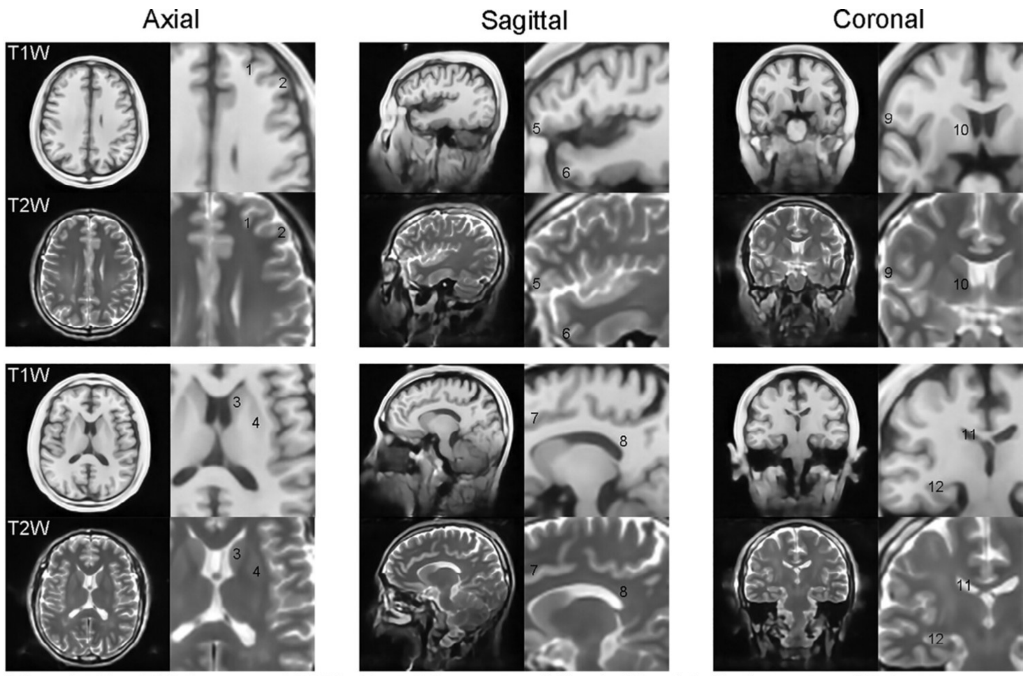

Figure 1: The contrast consistency of different brain tissues was assessed between T1W and T2W deep learning super-resolved 0.055T images from a healthy 27-year-old male volunteer. Two slices per orientation are presented. The intensity and delineation of gray matter, white matter, and cerebrospinal fluid structures show strong spatial alignment across both image types, suggesting that the details recovered through deep learning are genuine and not artifacts, as they consistently appear across independently generated outputs from two distinct contrast types [69].

Table 2: AI and radiomics in modern pathology.

Technology	Methodology	Clinical applications	Performance metrics	Advantages	Limitations	Future directions
Convolutional neural networks	Deep learning for image analysis	Tumor detection, segmentation	Accuracy: 92 - 96% (lung nodules)	Automates repetitive tasks; high accuracy	Requires large datasets; black box nature	Explainable AI integration
Radiomics analysis	Extraction of quantitative image features	Predicting treatment response, mutations	AUC: 0.75 - 0.89 (EGFR prediction)	Non-invasive biomarker discovery	Feature reproducibility challenges	Standardized feature extraction
Transformer models	Self-attention mechanisms	3D organ segmentation (e.g., SpineMamba)	Dice score: 0.91 - 0.94	Captures long-range dependencies	Computationally intensive	Lightweight transformer variants
Generative adversarial networks	Synthetic image generation	Data augmentation, modality translation	SSIM: 0.85 - 0.92 (MRI to CT)	Addresses data scarcity	Mode collapse risks	Federated learning applications
Graph neural networks	Analysis of relational data	Disease progression modeling	C-index: 0.71 - 0.82 (survival prediction)	Incorporates multi-modal data	Complex implementation	Dynamic graph learning

A study by Zhang et al. [71] presented significant findings regarding the diagnosis and analysis of Combined Pulmonary Fibrosis and Emphysema (CPFE) using advanced AI techniques. The researchers developed a deep learning-assisted diagnostic model named CPFENet, specifically designed for CPFE patients. This model utilizes 3D CT images to classify patients accurately into three categories: CPFE, chronic obstructive pulmonary disease (COPD), and pulmonary fibrosis. The diagnostic performance of CPFENet was found to be comparable to that of professional radiologists, indicating its potential as a reliable diagnostic tool. The study involved extracting radiomic features from the 3D CT images, which were then used to generate a CPFE score. This score serves as a robust and efficient metric for characterizing the presence of CPFE in patients. The ability to quantify CPFE through this scoring system enhances the understanding of the disease. The analysis revealed significant differences in CPFE scores between genders. This finding suggests that gender may play a role in the manifestation or severity of CPFE, which could have implications for personalized treatment approaches. To ensure the accuracy of their results, the researchers conducted a retrospective analysis of the gender distribution of patients across the participating hospitals. This validation process corroborated the findings related to CPFE scores and their differences between genders, reinforcing the reliability of the study's conclusions. Overall, this study represents the first multicenter systematic investigation of CPFE, providing a diagnostic model and clinical indicators that can facilitate accurate classification and characterization of the syndrome. The insights gained from this research are expected to guide future studies and potentially lead to the development of targeted therapeutic strategies, ultimately improving patient outcomes. These results highlight the potential of AI in enhancing the diagnosis and understanding of CPFE, paving the way for better management of this complex pulmonary condition [71].

A study by Tonneau et al. [72] aimed to evaluate the effectiveness of radiomics in predicting the response to immune checkpoint inhibitors in NSCLC patients. The research involved 642 advanced NSCLC patients, divided into a discovery cohort of 512 patients from three academic centers and a validation cohort of 130 patients from a fourth center. The study emphasized the importance of harmonizing CT scan images to account for variations in reconstruction kernels, slice thicknesses, and device manufacturers. This step was crucial for improving the generalizability of the radiomics models across different centers. The best prognostic factor for progression-free survival at 6 months was found to be the combination of clinical variables and PD-L1 expression, achieving an area under the curve (AUC) of 0.66 in the discovery cohort and 0.62 in the validation cohort. Without image harmonization, the combination of clinical variables with either PyRadiomics or DeepRadiomics yielded an AUC of 0.69 in the discovery cohort (Figure 2). However, this performance dropped significantly in the validation cohort, with AUCs of 0.57 and 0.52, respectively. This indicated a lack of generalizability. After applying image harmonization, the combination of clinical variables with DeepRadiomics achieved AUCs of 0.67 and 0.63 in the discovery and validation cohorts, respectively. In contrast, the combination of clinical variables with PyRadiomics did not perform well in the validation cohort, with AUCs of 0.66 and 0.59. The study concluded that a risk prediction model combining clinical variables with DeepRadiomics showed generalizability after CT scan harmonization. This model's performance was comparable to routine oncology practices using clinical variables and PD-L1 expression, highlighting the potential of radiomics as a non-invasive strategy for predicting immune checkpoint inhibitors response in advanced NSCLC. These results underscore the importance of harmonizing imaging data to enhance the reliability of radiomics in clinical applications [72].

A paper by Dercle et al. [73] presents several important findings regarding the application of AI and radiomics in the context of immunotherapy. The authors conducted a comprehensive literature review, identifying 351 studies related to AI and radiomics in immunotherapy. After filtering for relevance, 87 unique reports were included in their analysis. The median cohort size across the studies was 101 patients, with an interquartile range of 57 - 180. This indicates a moderate sample size, which is essential for the reliability of the findings. The primary objectives for developing radiomics models were categorized as follows: (i) prognostication: 29 studies (33.3%), (ii) treatment response prediction: 24 studies (27.6%), (iii) tumor phenotype characterization: 14 studies (16.1%), and (iv) immune environmental characterization: 13 studies (14.9%). A significant majority of the studies were retrospective (75 studies, 86.2%) and primarily conducted at single centers (57 studies, 65.5%). This suggests a need for more multicenter and prospective studies to enhance the generalizability of the findings. Among the studies that provided information on model testing,

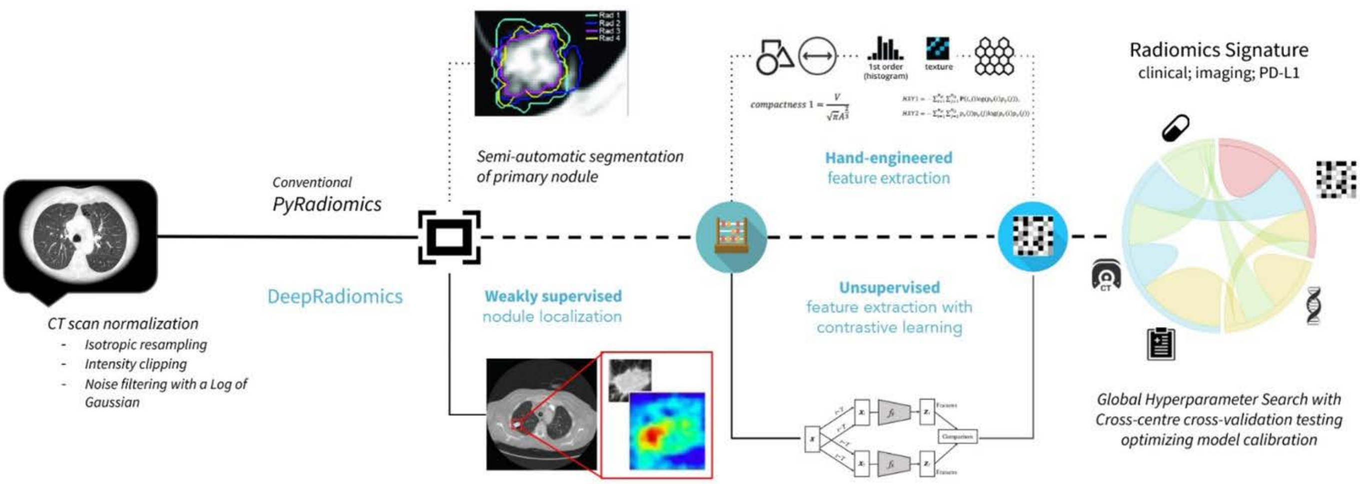

Figure 2: Radiomics workflows utilized in the study are illustrated in two parts. The top panel outlines the PyRadiomics pipeline, which involves segmentation input followed by the extraction of hand-crafted features. In contrast, the bottom panel depicts the DeepRadiomics pipeline, which employs weakly supervised region identification and automated feature extraction through deep learning methods [72].

54 (65.9%) utilized a validation set or better. The performance metrics were notably higher for radiomics signatures that predicted treatment response or tumor phenotype compared to those predicting immune environment and overall prognosis. The median Radiomics Quality Score was 12 out of a possible 36 points, with an interquartile range of 10 - 16. This indicates variability in the methodological quality of the studies reviewed, highlighting the need for standardization in data collection and analysis. The authors conclude that while there is a growing body of promising results indicating the potential of AI and radiomics to enhance precision medicine in cancer treatment, significant improvements in methodological quality and standardization are necessary before these findings can be effectively translated into clinical practice. These results underscore the potential of AI and radiomics in improving patient management in immunotherapy, while also pointing out the challenges that need to be addressed for clinical application [73].

While AI and radiomics hold promises for enhancing medical imaging and patient management, their clinical application is hindered by challenges in standardization, validation, and integration into existing clinical workflows. The variability in imaging modalities, cohort characteristics, and validation methods across studies underscores the need for standardized protocols and multicenter collaborations to ensure robust and generalizable findings. As these technologies continue to evolve, addressing these challenges will be crucial for their successful translation into clinical practice.

Challenges and Future Directions

Despite the significant advances in leveraging structural data for enhanced pathological precision, several challenges remain (Table 3). The lack of standardized imaging protocols and data formats can hinder the development and deployment of AI-based tools [48, 74]. The quality of imaging data can vary significantly, affecting the accuracy of diagnostic and prognostic predictions [48]. AI models trained on specific datasets may not generalize well to other populations or imaging modalities [48-50, 75]. The "black box" nature of some AI algorithms can make it difficult to understand how they arrive at their decisions [48].

Table 3: Challenges and future directions in imaging-pathology integration.

Category	Current challenges	Potential solutions	Clinical impact	Technological enablers	Timeline (Estimated)
Data standardization	Heterogeneous protocols across institutions	Development of universal imaging guidelines	Enables multi-center AI validation	DICOM standardization tools	2 - 5 years
Computational barriers	High GPU/resource demands	Edge computing; model compression	Facilitates real-time bedside analysis	Quantum machine learning	5 - 10 years
Clinical adoption	Resistance to AI-assisted diagnosis	Education; FDA-cleared AI tools	Improves diagnostic consistency	Integrated PACS/AI platforms	3 - 7 years
Anatomic-pathologic correlation	Disconnect between imaging and histology	Multimodal fusion algorithms	Enhances tumor microenvironment understanding	Spatial transcriptomics co-registration	5 - 8 years
Regulatory hurdles	Lack of clear AI validation frameworks	International consensus guidelines	Accelerates approval of AI tools	Blockchain-based validation	4 - 6 years

Future research should focus on addressing these challenges by developing standardized imaging protocols, improving data quality, and creating more interpretable AI models. Multicenter collaborations and extensive validation studies are crucial to ensure the applicability and generalizability of these technologies in diverse clinical settings [48]. Emerging trends in medical imaging include: (i) Multimodal imaging: Combining different imaging modalities, such as MRI and PET, can provide a more comprehensive view of disease processes [44, 76], (ii) Digital biobanks: Integrating imaging data with genomic, clinical, and pathological data can facilitate the sharing of curated and standardized information [74], (iii) Precision medicine: Leveraging imaging data to personalize treatment plans based on individual patient characteristics [22, 77, 78], (iv) Neural radiance fields: This technology offers enhanced visualization of anatomical structures in medical imaging where precise and detailed visualization is crucial [79], and (v) Surgical navigation: The use of 3D models derived from medical images for surgical simulations and navigation to enhance surgical precision [15, 16].

Conclusion

Leveraging structural data from clinical anatomy in imaging has the potential to significantly enhance pathological precision, leading to improved diagnostic accuracy, treatment planning, and patient outcomes. Advancements in imaging technologies, coupled with the integration of AI and radiomics, are driving this transformation. By addressing the challenges and embracing emerging trends, we can unlock the full potential of medical imaging to deliver more precise, personalized, and patient-centric care. Integrating holomics and AI in the management of patients represents a significant advancement in precision oncology. This innovative approach not only addresses the complexities of rare and aggressive diseases but also paves the way for global collaboration and equitable healthcare solutions, ultimately transforming the landscape of treatment and care of patients.

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Conflict of Interest

None.

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