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Deep Learning-Driven Multimodal Medical Imaging for Early Cancer Detection: Advances, Challenges, And Future Directions

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***Abstract*—Early cancer detection is a major determinant of patient prognosis, and artificial intelligence (AI), particularly deep learning (DL), offers transformative capabilities for image-based screening, diagnosis, and prognostication. This review synthesizes the current state of DL-based approaches applied to medical imaging for the early detection of cancer across various organ systems, with an emphasis on mechanisms, modalities, radiomics/radiogenomics, multimodal fusion, and their translation to clinical practice. We integrate evidence from systematic reviews, methodological surveys, and modality- and organ-specific studies to provide a cohesive picture of what works, where gaps remain, and how future developments may converge toward robust, generalizable, and clinically actionable solutions. Throughout, we emphasize the diversity of imaging modalities (ultrasound, CT, MRI, PET/CT) and the spectrum of DL-enabled tasks (detection, segmentation, radiomics feature extraction, radiogenomics integration, and multimodal fusion). We also discuss key challenges—data heterogeneity, reproducibility, external validation, and real-world deployment—and outline avenues for reproducible, multicenter collaboration. This synthesis draws on evidence from major reviews and primary studies spanning hepatobiliary, breast, gynecologic, head/neck, thyroid, prostate, and gastrointestinal cancers, highlighting both shared principles and domain-specific nuances [1]**

***Index Terms*—Deep Learning, Medical Imaging, Cancer Detection, Artificial Intelligence in Healthcare, Precision Oncology**

I. INTRODUCTION AND RATIONALE

The AI revolution in medical imaging centers on DL, which can automatically learn hierarchical representations from large image cohorts, reducing reliance on hand-crafted features and enabling end-to-end learning for detection, segmentation, and classification tasks. Foundational reviews document a broad shift from traditional machine learning toward DL in cancer imaging, underscoring improved performance for lesion detection, characterization, and treatment response assessment across CT, MRI, ultrasound, and PET modalities [1], [15], [21], [20]. The literature also notes that, while DL methods are powerful, rigorous prospective validation and reproducibility remain active areas of development [1], [15], [22].

Radiomics—the extraction of high-dimensional quantitative image features followed by machine learning—provides a bridge between imaging phenotypes and biological processes. Radiomics has proliferated in oncology, with DL-based radiomics emerging as a means to improve discrimination, prognosis, and response prediction across cancers and imaging modalities [7], [9], [10], [23], [15], [20]. Integrating radiomics with genomics (radiogenomics) is an active frontier that promises more precise, biology-informed imaging biomarkers and decision support [9], [20].

The scope of DL in cancer imaging spans many organ systems and imaging modalities. Abdominal imaging, including hepatobiliary diseases, has seen DL-driven gains in lesion detection, segmentation, and microvascular invasion (MVI) prediction; breast, gynecologic, head/neck, thyroid, prostate, and other GI cancers likewise benefit from DL and radiomics approaches. Integrated reviews specifically covering hepatocellular carcinoma (HCC) and intrahepatic cholangiocarcinoma (ICC) illustrate the growth of DL/radiomics in liver cancer detection, characterization, and prognosis, while broader reviews document DL's clinical translation challenges and opportunities across cancer imaging [1], [4], [6]

II. CORE DL METHODS FOR EARLY CANCER DETECTION IN MEDICAL IMAGING

Convolutional neural networks (CNNs) and 3D CNNs have become standard for lesion detection and segmentation in CT, MRI, ultrasound, and PET data. Early DL studies demonstrated high performance in lesion classification and segmentation tasks (e.g., MRI liver lesion classification with high accuracy, sensitivity, and specificity in CNN-based systems) and then extended to volumetric 3D CNNs for CT/MRI image analysis. These advances are documented across hepatobiliary cancer literature and broader DL/image-analysis surveys [1], [4], [15], [18].

Radiomics and radio genomics complement DL by enabling handcrafted or learned feature representations that can be combined with ML or DL classifiers. Radiomics workflows include feature extraction from delineated regions of interest (ROIs), followed by feature selection and model building; more recent work fuses radiomic features with DL-derived representations to improve performance in tumor diagnosis, prognosis, and treatment response prediction across multiple cancers [7], [9], [23], [15], [20].

Multimodal and radiology-genomics integration (multimodal DL) is an influential direction enabling joint use of imaging and molecular data for improved diagnostic and prognostic accuracy. Early and intermediate fusion frameworks, as well as late fusion approaches, have been explored in radiology-genomics contexts, showing promise for precision oncology and better capturing tumor biology than single-modality analyses [9], [19], [20]. The literature emphasizes both the potential gains and the methodological challenges of multimodal integration, including alignment, normalization, data availability, and interpretability [9], [19], [20].

Transfer learning and data-efficient DL strategies are frequently employed to address limited annotated medical imaging data, particularly in hepatobiliary and gynecologic domains. Foundational discussions emphasize the role of transfer learning to adapt pre-trained networks to medical imaging tasks and the importance of careful validation to avoid overfitting in small-sample settings [15], [24]

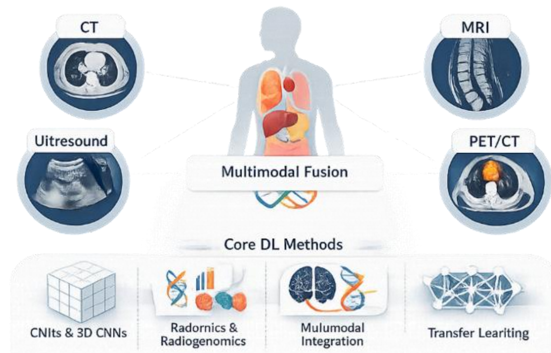

Figure 1 Core deep learning techniques for early cancer detection, including CNNs, radiomics, multimodal learning, and transfer learning.

III. ORGAN- AND MODALITY-FOCUSED EVIDENCE FOR EARLY DETECTION

3.1. Hepatobiliary Cancers (HCC and ICC)

HCC detection, characterization, and prognosis benefit from AI-assisted analysis of imaging and radiomics features across CT, US, MRI, and PET. Systematic reviews summarize a substantial body of work applying AI to HCC imaging, with improvements in lesion detection and differential diagnosis, but with emphasized need for prospective validation and awareness of bias in retrospective designs [1], [11]. In particular, MRI-based CNNs have demonstrated strong performance in liver lesion classification; DL systems can achieve high accuracy and rapid inference on MRI data, though heterogeneity of lesions and borders complicates segmentation [1], [11].

Preoperative prediction of microvascular invasion (MVI) in HCC using imaging-derived DL and radiomic features has emerged as a clinically important problem, given MVI's impact on recurrence and survival. Three-dimensional CNN models trained on CT or MRI have shown promising discrimination of MVI status, with reported AUC values approaching or exceeding 0.9 in validation cohorts, highlighting the potential for noninvasive tailoring of surgical or adjuvant strategies [8], [8], [7].

Radiomics-focused syntheses emphasize that CT- and MRI-based radiomic signatures, including those fused across sequences or combined with clinical factors, can improve MVI prediction and survival modeling in HCC, and that radiomics may offer added value beyond conventional imaging interpretations [7], [18].

Comprehensive reviews on HCC radiomics and AI-based radiomics summarize the current state and outline methodological pitfalls that impede translation, including standardization of imaging protocols, ROI delineation, and feature reproducibility [18], [7].

ICC, as another major hepatobiliary cancer, has seen radiomics-based prognosis modeling using intrahepatic lesions, with radiomics features and ML/DL methods used to predict lymph node status, microvascular invasion, and recurrence risk. Radiomics and MDL approaches are described in contemporary reviews and primary ICC studies, illustrating the broader applicability of image-derived features to cholangiocarcinoma biology [7], [2], [9].

3.2. Breast Cancer

Imaging-based AI for breast cancer encompasses detection, segmentation, and characterization via mammography, ultrasound, MRI, PET/CT, and integrated PET/MRI. Reviews and surveys summarize how AI, ML, and DL have advanced lesion detection, segmentation, and classification across modalities, while acknowledging the need for clinical validation and interpretability in routine practice [3], [6], [5], [25], [21].

DL-based radiomics and multimodal fusion are particularly active in breast cancer, with studies showing high-performance classifiers for distinguishing malignant from benign lesions on ultrasound, MRI, and tomosynthesis, as well as for predicting treatment response to neoadjuvant chemotherapy and prognosis. Reviews highlight that fusion imaging (e.g., MRI with PET/CT/MRI) can improve detection and staging and that radiomics features can be combined with clinicopathologic data to enhance predictive performance [3], [6], [5], [16], [25], [10].

The practical challenge for breast imaging AI includes ensuring model interpretability, handling heterogeneous imaging data, and validating models across multicenter cohorts to ensure generalizability. Reviews emphasize that AI is unlikely to replace radiologists but can substantially augment detection, segmentation, and decision support in breast cancer imaging when integrated into clinical workflows [5], [6], [3], [25], [10].

3.3. Gynecologic Cancers and Imaging for Early Detection

Gynecologic malignancies rely on ultrasound, MRI, CT, and PET-CT for staging and management, with radiomics and DL approaches increasingly used to improve localization and characterization. Consensus statements and reviews underscore ultrasound's role as a first-line imaging modality in gynecologic cancer workups, alongside MRI and CT, while noting that advanced functional imaging (e.g., PET-CT) provides complementary information for nodal and distant disease assessment. Early-stage and preoperative imaging staging benefit from standardized ultrasound assessment and selective use of PET-based modalities [26], [27], [28]. Studies discuss the role of radiomics and DL in differentiating benign vs malignant gynecologic lesions and in assessing treatment response, with ongoing exploration of fusion imaging and radiomics-based biomarkers for prognosis and recurrence risk [27], [26], [3].

In breast-gynecologic oncologic imaging contexts, radiomics and MDL approaches increasingly enable noninvasive prediction of tumor biology, microenvironment characteristics, and response to therapy, supporting personalized management in gynecologic cancers as in other organs [9], [19], [10].

3.4. Head and Neck Cancers

Head and neck cancers (HNC) rely on ultrasound, CT, MRI, and PET for staging, with radiomics and DL increasingly applied to assess nodal status, tumor extent, and recurrence risk. Reviews emphasize that radiomics features from CT/MRI/PET, possibly combined with clinical data, can improve prediction of nodal metastasis and treatment outcomes, although external validation remains imperative. DL-based radiomics approaches for lymph node status and prognosis are actively studied, and radiomics is highlighted as a growing tool in HNC management [17], [13], [29].

In addition to static imaging, dynamic and functional MRI techniques (e.g., diffusion-weighted imaging, perfusion) have potential to quantify tissue microenvironmental changes and treatment-related toxicity, with radiomics-based analyses providing prognostic insights in HNC survivorship and late effects [29].

3.5. Prostate and Thyroid Cancers

In prostate cancer, radiomics and DL continue to be developed for lesion detection, grading, and outcome prediction, with mpMRI and PSMA-PET data frequently integrated in multisource models to improve lesion characterization and risk stratification; reviews summarize current radiomic methodology and the potential for future integration with molecular data to improve personalized management [14], [14].

In thyroid cancer and nodules, radiomics-based DL approaches have been explored for improving the differentiation of malignant vs benign nodules in ultrasound, CT, and MRI, with radiomics found to potentially enhance classification performance beyond conventional imaging alone in some studies; however, inconsistencies in study design and patient cohorts require cautious interpretation [30].

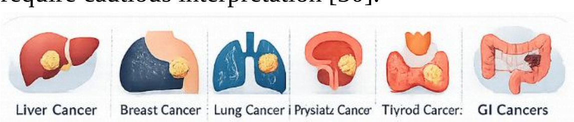

Figure 2 Applications of deep learning in cancer detection across multiple organ systems using multimodal medical imaging.

IV. RADIOMICS, RADIOGENOMICS, AND MULTIMODAL FUSION

Radiomics has become a mature subfield within DL for oncology imaging, enabling high-throughput extraction of quantitative features from CT, MRI, US, and PET images to power tumor classification, prognosis, and treatment response modeling. The reviewed literature documents substantial progress, including MDL frameworks that fuse radiomics with clinical variables or with genomics data to improve predictive accuracy and to provide mechanistic insight into tumor biology [7], [9], [10], [23], [15], [19], [20].

Radiogenomics — linking imaging phenotypes to genomic and molecular features — is increasingly pursued to noninvasively infer tumor biology and predict outcomes. MDL frameworks enabling radiology-genomics integration are discussed as a promising direction for precision oncology, though methodological challenges remain (data alignment, standardization, interpretability) [9], [19], [20].

Multimodal DL strategies—early, intermediate, and late fusion of imaging modalities and molecular data—have shown potential to outperform single-modality approaches in tumor detection, staging, and prognosis, particularly when large, heterogeneous datasets are available. Foundational reviews emphasize both the opportunities and the practical hurdles to clinical translation, including data heterogeneity, reproducibility, and regulatory considerations [9], [19], [20].

V. CHALLENGES IN TRANSLATION TO CLINICAL PRACTICE

Data availability and quality: Wide variability in imaging protocols, scanners, acquisition parameters, and annotation practices can hamper model generalizability. Multicenter datasets and shared repositories are repeatedly called for to enable robust external validation and reproducibility of DL/radiomics models [1], [11], [15], [18], [20].

Validation and generalizability: The predominance of retrospective studies raises concerns about bias and applicability in varied clinical settings. Prospective trials, standardized protocols, and open reporting of performance metrics are emphasized across hepatobiliary, breast, and other cancer imaging DL studies [1], [15], [11], [18], [20].

Interpretability and clinical integration: Although DL models offer high predictive performance, clinicians require interpretable outputs, risk explanations, and integration into existing workflows. Reviews highlight interpretability challenges and discuss strategies such as radiomics feature interpretability and model-agnostic explanations to foster trust and adoption [6]

Regulatory and ethical considerations: As AI-driven radiology tools approach clinical deployment, questions of data governance, bias, patient privacy, and regulatory approval become central, with expert recommendations on best practices for safe and responsible AI in oncology imaging [15], [21], [20].

Figure 3 Key challenges and future directions in AI-based cancer imaging, emphasizing data heterogeneity, validation, and clinical integration.

VI. IMPLICATIONS FOR PRACTICE AND FUTURE DIRECTIONS

Integrated, multimodal DL frameworks that combine imaging (CT/MRI/US/PET), clinical data, and – where available – genomic information are poised to deliver the most value in early cancer detection, risk stratification, and dynamic treatment planning. Multimodal DL and radiomics-radiogenomics fusion are repeatedly identified as the most promising avenues to achieve precision oncology in imaging [9], [19], [20].

Standardization and data sharing will be essential to unlock generalizable DL/adaptive radiomics models. Collaborative, multicenter studies and open validation datasets will accelerate translation from research to clinical practice, with the potential for improved early detection, more accurate staging, and personalized treatment decisions across cancer types [1], [15], [18], [20].

Ongoing work on interpretability, user-centric design, and seamless integration with radiology workflows will be critical to clinician acceptance and real-world impact, especially in high-volume screening settings such as breast cancer imaging and liver lesion evaluation [6], [3], [5], [25].

VII. CONCLUSIONS

The body of evidence indicates that deep learning, radiomics, and radiogenomics have collectively transformed the landscape of cancer imaging for early detection and prognosis. Across organ systems and imaging modalities, DL-based lesion detection, segmentation, and radiomics-based predictive models demonstrate strong promise, with many studies reporting high performance metrics in retrospective cohorts. However, to realize widespread clinical impact, the field must advance prospective validation, multicenter collaboration, standardization, and transparent reporting to ensure reproducibility and generalizability. The convergence of DL with radiomics and radiogenomics—augmented by robust multimodal fusion strategies—represents a compelling pathway toward precision oncology in imaging [1]., [4], [6], [7], [8], [9], [10], [11], [14], [15], [16], [17], [18], [19]

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