Physical Education, Health and Social Sciences

https://journal-of-social-education.org E-ISSN: 2958-5996

P-ISSN: 2958-5988

Artificial Intelligence-Based Diagnostic Models for Early Detection of Cancer Using Medical Imaging

Taib Ali*[1], Imtiaz Ali[2], Ghulam Yasin[3]

[1] Department of Computer Science, University of South Asia.
*Corresponding Author Email: taibali303@gmail.com
[2] Department of Computer Sciences Lasbela University of Agriculture, Water and Marine science
Email: imtiazalib75@gmail.com
[3] Department of Computer Science, University of Makran Panjgur. yasinarman38@gmail.com
Ghulam.yasin@uomp.edu.pk

DOI: https://doi.org/10.63163/jpehss.v4i1.1129

Abstract

The rapid advancement of artificial intelligence (AI), particularly deep learning architectures such as Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), and hybrid models, has fundamentally transformed early cancer detection using medical imaging. This comprehensive review synthesizes recent developments in AI-based diagnostic models across major cancer types (breast, lung, prostate, pancreatic, and others), highlighting their superior or comparable performance to human radiologists in sensitivity, specificity, and early-stage lesion identification. Landmark prospective trials (MASAI study) and large-scale validations (e.g., Sybil model for lung cancer risk prediction) demonstrate that AI can significantly improve screening sensitivity, reduce inter-observer variability, and enable non-invasive radiogenomic phenotyping. Key innovations include multi-modal data fusion (radiomics + genomics), generative models (diffusion models for data augmentation and tumor progression simulation), foundation models for cross-modality learning, federated learning for privacy-preserving collaborative training, and explainable AI (XAI) techniques (heatmaps, SHAP, attention visualization) to build clinical trust. Despite these advances, persistent challenges remain, including workflow integration, alert fatigue, algorithmic bias, liability allocation, regulatory compliance (FDA clearances, EU AI Act), and reimbursement pathways. The paper concludes that AI is transitioning from an assistive tool to a core component of precision oncology, with future success dependent on robust external validation, bias mitigation, seamless PACS integration, and interdisciplinary collaboration between clinicians, data scientists, and regulators.

Keywords: Artificial intelligence, medical imaging, early cancer detection, deep learning, convolutional neural networks, vision transformers, radiomics, radiogenomics, federated learning, explainable AI, breast cancer screening, lung cancer risk prediction, diffusion models, precision oncology

1. Introduction

The integration of artificial intelligence (AI) into the clinical landscape of oncology represents one of the most significant paradigmatic shifts in modern medicine (Huang et al., 2025). This transformation has been driven by the rapid transition from basic computer-aided detection (CAD) systems to sophisticated deep learning architectures capable of mimicking, and in some cases exceeding, human cognitive performance in specific diagnostic tasks (Beyer et al., 2025). Historically, the application of AI in radiology was characterized by logic-based expert systems developed in the mid-20th century. These early iterations followed rigid "if-then" rules that, while mathematically sound, proved insufficient for the complex and heterogeneous nature of clinical imaging (Ng & Leung, 2025). The emergence of machine learning in the late 1950s and 1960s ignited a more data-centric approach, yet it was the advent of deep learning in late 2012 that catalyzed the current explosion in imaging informatics (Yu, 2020). This pivotal moment was marked by a convolutional neural network (CNN) winning the ImageNet Classification competition, demonstrating that models could learn abstract representations directly from raw data without the need for manual feature engineering (Khan et al., 2020).

the impact of these technical milestones was quantifiable, with approximately 70% of the 343 United States Food and Drug Administration (FDA) approved AI products being specifically developed for radiology and radiation oncology (Khunte et al., 2023). This trend has continued into 2025, with hundreds of AI-enabled tools now possessing regulatory clearance for tasks ranging from preliminary report drafting to complex lesion classification (Harvey et al., 2020). A survey conducted in 2024 by the European Society of Radiology revealed that nearly half of its members have already integrated AI into their clinical practice, underscoring a rapid global adoption (Potnis et al., 2020). The market for imaging science has expanded in parallel, driven by new clinical indications involving proteomic and genomic expressions that demand more robust analytical tools than traditional visual inspection can provide (Milam et al., 2023).

The transition from conventional machine learning to deep learning is fundamental to understanding the current state of early cancer detection. Traditional machine learning typically required radiologists to manually segment regions of interest and extract quantitative features a process known as radiomics before these features were fed into a classifier (Dixit et al., 2023). In contrast, deep learning architectures automatically learn hierarchical representations of the data. This allows the models to identify sub-visual patterns in texture, intensity, and spatial relationships that are often imperceptible to the human eye, facilitating the detection of malignancies at their earliest, most treatable stages (Benning et al., 2022).

2. Architectural Foundations and Computational Frameworks

The effectiveness of diagnostic models for cancer detection is rooted in the mathematical and structural diversity of neural networks. While Convolutional Neural Networks (CNNs) have long served as the cornerstone of medical image analysis, the current frontier is defined by the emergence of Vision Transformers (ViTs) and hybrid systems (Takahashi et al., 2024).

2.1 Convolutional Neural Networks and Hierarchical Feature Extraction

CNNs are designed to process data with a grid-like topology, making them inherently suited for image analysis. They utilize convolutional layers where kernels or filters slide over the input image to identify local patterns such as edges, blobs, and textures (Pal et al., 2025). As the data progresses through deeper layers, the model aggregates these local features into more complex representations of anatomical structures and pathological lesions (Martinez et al., 2023).

A critical advancement in this space is the U-Net architecture, which has become the standard for medical image segmentation (Neha et al., 2024). U-Net utilizes a symmetric encoder-decoder structure the encoder path captures the contextual information of the image by reducing spatial dimensions, while the decoder path recovers the spatial resolution through up-convolution, allowing for precise pixel-wise localization of tumor boundaries (Azad et al., 2024). Skip connections between the encoder and decoder levels ensure that fine-grained spatial details are not

lost during the down-sampling process, which is essential for delineating small or irregularly shaped tumors in CT or MRI scans (Shi et al., 2024).
he performance of medical image segmentation models is commonly evaluated using quantitative metrics that reflect their diagnostic and clinical utility. One of the most widely used metrics is the Dice Similarity Coefficient (DSC), which measures the degree of overlap between the model's predicted segmentation and the manually annotated ground truth (Wong et al., 2024). The Dice coefficient can be mathematically expressed as:

$$\text{DSC} = \frac{2 \times | X \cap Y |}{| X | + | Y |}$$

where **X** denotes the predicted segmentation and **Y** represents the ground truth annotation (Yu, 2020). A high DSC value indicates strong agreement between automated and manual segmentations, which is particularly critical in clinical applications such as radiotherapy planning. Accurate tumor delineation ensures optimal radiation dose delivery to malignant tissues while minimizing exposure to surrounding healthy organs, thereby improving treatment efficacy and patient safety (Taciuc et al., 2025).

2.2 Vision Transformers and Global Contextual Awareness

Despite their success, CNNs possess inherent limitations, particularly regarding their receptive field. Because convolution is a local operation, traditional CNNs struggle to capture long-range dependencies relationships between distant pixels that may be clinically significant in large or complex medical images (Younesi et al., 2024). Vision Transformers address this by adapting the self-attention mechanisms originally developed for natural language processing (Zhong et al., 2025).
In a Vision Transformer (ViT) architecture, an input image is first partitioned into a set of fixed-size patches, with each patch treated as an individual token in a sequential input representation (Li et al., 2023). Unlike convolutional neural networks, which rely on local receptive fields, ViTs employ a self-attention mechanism that enables the model to dynamically assign importance weights to each patch relative to all other patches, irrespective of their spatial distance. This mechanism allows the model to capture global contextual relationships, providing a comprehensive understanding of anatomical structures within the image (Habib et al., 2024).
The self-attention operation is computed using the Query (Q), Key (K), and Value (V) matrices as follows:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

where $d_k$represents the dimensionality of the key vectors. This global representation capability is particularly beneficial for medical imaging tasks, as it facilitates the detection of **multi-focal disease patterns** and subtle secondary indicators of malignancy that may appear distant from the primary lesion (Sarkar et al., 2022).

Table 1. Comparison of AI Model Architectures in Oncological Imaging

Architecture Type	Key Mechanism	Primary Advantage	Typical Limitation
CNN (e.g., U-Net)	Local convolution kernels	Excellent local feature extraction; data efficiency (Pal et al., 2025)	Limited global context (Pal et al., 2025)

Transformer (e.g., Swin)	Self-attention over patches	Captures global relationships and context (Pal et al., 2025; Takahashi et al., 2024)	Requires larger datasets and more compute (Pal et al., 2025)
Hybrid (e.g., ViT-DCNN)	Combined attention and convolution	Learn both holistic context and fine-grained detail (Pal et al., 2025)	High architectural complexity (Pal et al., 2025)
GAN / Diffusion	Probabilistic reconstruction	Synthetic data generation; image denoising (Beyer et al., 2025; Zhang et al., 2025)	Risk of "hallucinations" (Beyer et al., 2025)

2.3 Hybrid Models and Deformable Convolutions

The current research trajectory favors hybrid models that integrate the local precision of CNNs with the global modeling capabilities of Transformers (Alomar et al., 2025). For instance, the ViT-DCNN (Vision Transformer with Deformable CNN) model utilizes deformable convolutions to account for the non-rigid nature of anatomical structures, while the self-attention layers maintain a broad contextual window (Pfeiffer et al., 2020). On benchmark test sets, this hybrid approach has demonstrated an accuracy of 94.24% in detecting lung and colon cancer, outperforming several standalone architectures including ResNet-152 and SwinTransformer (Zheng et al., 2021).

3. Radiomics, Radiogenomics, and Multi-modal Data Fusion

Early detection of cancer is increasingly viewed not as a single-modality challenge but as a task requiring the synthesis of multiple heterogeneous data streams. Multi-modal AI models consolidate genomic, transcriptomic, proteomic, imaging, and clinical metadata into unified analytical frameworks (Vincenzo, 2024). This integrative approach, often termed radiogenomics, provides a more biologically faithful representation of tumor heterogeneity than any single modality could offer (Simon et al., 2025).

3.1 The Mechanism of Information Fusion

In the context of oncology, information fusion can be categorized into three primary strategies: early fusion, late fusion, and hybrid fusion. Early fusion, or feature-level fusion, involves concatenating features from different modalities (e.g., radiomic features from a CT scan and mutational data from a biopsy) before they are fed into a single predictive model (Yuan et al., 2025). This allows the AI to learn joint representations across different data types from the start. However, this strategy is susceptible to overfitting because of the high dimensionality of the combined datasets and the potential lack of modality-specific preprocessing (Nam et al., 2024).

Late fusion, or decision-level fusion, processes each modality through an independent sub-network. The outputs or individual predictions from these networks are only combined at the final decision stage (Joshi et al., 2021). This approach is modular and more robust, as clinicians can audit the contribution of each modality to the final diagnosis. It is particularly effective when the quality of data across modalities is inconsistent (Messiou et al., 2021).

Hybrid fusion attempts to capitalize on the strengths of both early and late fusion by combining features at multiple levels of the network architecture (Ayantayo et al., 2023). Research consistently indicates that hybrid models, often utilizing attention mechanisms or graph neural networks, demonstrate superior performance in complex tasks such as predicting patient survival or identifying specific molecular subtypes (Gadzicki et al., 2020).

3.2 Radio genomics and Phenotypic Correlation

Radio genomics explores the relationship between the imaging phenotypes of a tumor (the "radio type") and its underlying genomic expression (Lo Gullo et al., 2020). For example, studies in breast cancer have demonstrated that AI-extracted radiomic features can correlate with clinically relevant genomic alterations, effectively providing a "virtual biopsy" that is non-invasive and can be performed repeatedly during the course of treatment (Fathi Kazerooni et al., 2020).

In neuro-oncology, the integration of MRI data with epigenomic profiles has been successful in predicting the methylation status of the O6-methylguanine-DNA methyltransferase (MGMT) promoter in glioblastoma patients (Ayus & Jena, 2025). Identifying this status is critical for determining the efficacy of alkylating chemotherapy, illustrating how AI-based diagnostic models directly influence personalized treatment strategies (Saxena et al., 2023).

4. Organ-Specific Clinical Performance and Meta-Analyses

The clinical utility of AI-based diagnostic models has been validated across several major cancer types, with performance often matching or exceeding that of specialized radiologists in enriched reader studies and prospective trials (Alis et al., 2025).

4.1 Breast Cancer: Landmark Studies and Triage Models

Breast cancer screening has seen the most extensive validation of AI. The MASAI (Mammography Screening with Artificial Intelligence) study, a randomized, controlled trial involving over 100,000 women, demonstrated that AI-supported screening was non-inferior to standard double reading by two radiologists (Hernström et al., 2025). Specifically, the AI-supported group showed a screening sensitivity of 80.5%, compared to 73.8% in the double-reading group (P = 0.031), without a significant increase in the recall rate (Gommers et al., 2026).

A major retrospective study published in The Lancet Digital Health utilized a dataset of over 170,000 examinations to train an algorithm that demonstrated superior sensitivity in detecting several critical cancer types (Kim et al., 2020)..

Table 2. Comparison of AI and Radiologist Sensitivity for Specific Early Breast Cancer Findings

Clinical Finding	AI Sensitivity	Radiologist Sensitivity	Statistical Significance (p-value)
T1 Cancers (Small Tumors)	91.0%	74.0%	0.0039 (Kim et al., 2020)
Node-Negative Cancers	87.0%	74.0%	0.0025 (Kim et al., 2020)
Mass-Type Lesions	90.0%	78.0%	0.044 (Kim et al., 2020)
Distortion or Asymmetry	90.0%	50.0%	0.023 (Kim et al., 2020)

The standalone performance of the AI in this study reached an AUROC of 0.959. Crucially, the diagnostic performance of radiologists significantly improved when they utilized the AI as a support tool, with their average AUROC rising from 0.810 to 0.881 (Pesapane et al., 2025). This finding supports the "autopilot" model of AI, where the technology augments human expertise rather than replacing it (Beyer et al., 2025).

4.2 Lung Cancer: The Shift to Image-Based Risk Prediction

In lung cancer, the focus of AI research has shifted from simple nodule detection to global risk prediction based on low-dose CT (LDCT) scans (Cellina et al., 2023). While traditional tools were "nodule-centric," focus has turned to models like Sybil, which analyzes the entire LDCT scan to predict an individual's risk of developing lung cancer over the subsequent six years (Arshad et al., 2025). Sybil does not require clinical history or smoking data, relying solely on the visual information in the scan to identify sub-visual patterns indicative of future malignancy (Mayfield et al., 2026).

Sybil has been validated in more than 120,000 LDCT scans across 25 hospitals globally (Cai et al., 2024). Notably, while the model was initially trained on a dataset that was 91% White, subsequent validation in a predominantly Black cohort and an East Asian population showed it to be race- and ethnicity-agnostic, addressing a critical concern regarding algorithmic bias in diverse global settings (Pierre, 2024).

4.3 Prostate and Pancreatic Cancer: Reducing Variability and Improving Accuracy

For prostate cancer, AI models are integrated into the MRI workflow to assist in lesion detection and PI-RADS (Prostate Imaging-Reporting and Data System) scoring. A meta-analysis of AI performance in prostate MRI reported a pooled sensitivity of 0.87, compared to 0.85 for radiologists (Patel et al., 2023). The primary benefit in this domain is the reduction of inter-observer variability, which can range significantly among human readers. By providing more consistent interpretations, AI models help reduce unnecessary biopsies (Quinn et al., 2023).

Pancreatic cancer detection has also seen breakthroughs through the integration of AI with endoscopic ultrasound (EUS) and non-contrast CT. A model named PANDA achieved an AUROC between 0.986 and 0.996 in multicenter validation for lesion detection in non-contrast CT scans (Lappas et al., 2022). This capability is particularly vital for patients who have contraindications for intravenous contrast, offering a high-accuracy diagnostic alternative (Zhang et al., 2025).

5. Generative AI and Foundation Models in Imaging

The most recent advancements in oncological AI involve the use of generative models and foundation models to address data scarcity and improve image quality (Tarhini r et al., 2025).

5.1 Diffusion Models for Synthesis and Progression

Diffusion models represent a new class of generative AI that works by progressively transforming data into noise and then learning to reverse this process (Bengesi et al., 2024). Unlike Generative Adversarial Networks (GANs), which can be unstable during training, diffusion models provide a more stable optimization objective and generate high-quality, detailed samples (Hadiyya et al., 2025).

In the context of cancer research, diffusion models are being used to synthesize photorealistic medical images to augment training datasets for rare cancers where real-world images are limited. For example, the "SkEditTumor" framework uses a sketch-based diffusion model to visualize tumor progression (Kidder, 2024). By using sketches as structural priors, clinicians can generate realistic simulations of how a tumor might evolve, enhancing communication between experts and improving a patient's understanding of their prognosis (Osorio et al., 2024).

5.2 Foundation Models and Cross-Modality Learning

Foundation models are large-scale neural networks pre-trained on vast, often unlabeled datasets (Hosseini et al., 2025). These models can be fine-tuned with relatively small amounts of labeled medical data to perform diverse diagnostic tasks. They are helping to mitigate the "training bias" associated with smaller datasets and are improving the ability of AI systems to generalize across different populations and imaging hardware (Sufian et al., 2024).

In 2025, these models represent the "frontier" of radiology AI, as they can link images with clinical text or EHR data more effectively than previous generations (Mottez et al., 2025). For example, early versions of EHR-aware AI can analyze a chest CT while simultaneously considering the patient's age, laboratory results, and prior clinical history to generate risk-adjusted interpretations (Jiao et al., 2021).

6. Federated Learning and Privacy-Preserving Collaborative Training

A significant hurdle in developing high-performing AI models for cancer detection is the need for massive, diverse datasets, which are often siloed within individual hospitals due to privacy concerns. Federated learning (FL) has emerged as a decentralized approach that enables collaborative model training across multiple institutions without ever sharing raw patient data (Sharif et al., 2024).

6.1 The Paradigm of Federated Training

In a federated learning architecture, each participating site trains a local model on its own private data. Instead of sending the images to a central server, only the model updates such as weights or gradients are exported. A central server then aggregates these updates to refine a global model (Koutsoubis et al., 2025).

6.2 Privacy Risks and Mitigation Strategies

Despite its benefits, federated learning is not entirely immune to information leakage. Attackers can potentially reconstruct sensitive images from gradient updates through "model inversion" attacks. To counter this, advanced FL frameworks integrate additional techniques (Fang et al., 2024)

Platforms like the Federated Learning Interoperability Platform (FLIP) are currently being deployed within health systems like the UK's NHS to enable secure, multi-modal data engineering and AI training without transferring patient data outside hospital boundaries (AI Centre for Value Based Healthcare, 2025).

7. Explainability and Clinician Trust: The Role of XAI

The "black-box" nature of deep learning models has historically hindered their clinical acceptance. Explainable AI (XAI) is a subfield of AI that focuses on making the inner workings of these algorithms transparent and interpretable (Hassija et al., 2024).

7.1 Techniques for Interpretable Diagnosis

XAI employs various techniques to illuminate the high-level reasoning of a model:

- Saliency Maps and Heatmaps: Tools like Grad-CAM++ generate pixel-level heatmaps that highlight the specific regions of an image that influenced the model's prediction. This allows a radiologist to verify that the AI is focusing on the actual lesion (Zou & Miao, 2025).
- SHAP and Attention Visualization: Techniques such as SHAP (SHapley Additive exPlanations) can quantify the relative contribution of different modalities in a multi-modal model (Yuan et al., 2025).
- Human-AI Dialogue: The future of XAI involves a shift from static explanations to a genuine dialogue between the AI system and the medical professional. In this paradigm, the AI could justify its contributions and respond to context-dependent queries, facilitating a more collaborative decision-making process (Beyer et al., 2025).

Integrating XAI into the clinical workflow is essential for identifying and mitigating bias. Furthermore, by revealing the specific features that contribute to a prediction, XAI can accelerate the discovery of new imaging biomarkers for cancer prognosis (Neha et al., 2024).

8. Regulatory Pathways and the 2026 Economic Landscape

The successful implementation of AI diagnostic models depends on a stable regulatory framework and clear reimbursement strategies (Lo Gullo et al., 2020).

8.1 The Regulatory Evolution: FDA and EU AI Act

The FDA continues to field an increasing number of AI device submissions, with 2025 seeing the highest number of authorizations in the agency's history. Most approved tools are "narrow AI" focused on specific clinical tasks, while generative models remain largely in the research phase due to validation concerns (MedTech Dive, 2026).

By 2026, the EU AI Act is expected to categorize radiology AI as "high-risk," imposing strict requirements for training data transparency and human oversight. This regulatory scrutiny is pushing developers to conduct more rigorous external validation and to document potential algorithmic drift (Ayus & Jena, 2025).

8.2 Reimbursement and the Value-Based Model

Medicare and other payers are beginning to establish formal reimbursement pathways for AI-enabled services (Hernström et al., 2025).

- Hospital OPPS 2026: The 2026 Hospital Outpatient Prospective Payment System (OPPS) Final Rule established national reimbursement under the Outpatient Prospective Payment System (OPPS) specifically for AI-assisted cardiac analyses, providing a blueprint for oncology (Hernström et al., 2025).

Economic Impact: While the upfront cost of AI implementation is high, the net economic effect is projected to be positive (Zhong et al., 2025).

Health economists estimate that AI could save billions annually by reducing unnecessary procedures and identifying cancers at earlier stages where treatment is significantly less expensive (Wong et al., 2024).

9. Implementation Challenges and Future Directions

Despite the promising performance of AI-based diagnostic models, several challenges remain for their integration into routine oncology practice (Nam et al., 2024).

9.1 Clinical Workflow and Integration

A primary barrier is the disruption of existing clinical workflows. If an AI tool adds extra steps, it faces resistance from busy radiologists. "Alert fatigue" is a recognized risk, where excessive AI-generated notifications lead to clinician desensitization (Simon et al., 2025). Future systems aim to integrate directly into Picture Archiving and Communication Systems (PACS) and use "smart worklist prioritization" to flag urgent cases (Alis et al., 2025).

9.2 The Liability Gap

Liability remains a complex legal challenge. Courts have not yet definitively resolved who is responsible if an algorithm misses a diagnosis the healthcare organization, the physician, or the software developer (Taciuc et al., 2025). A core principle currently emerging is that physicians must retain ultimate responsibility for patient care decisions and cannot delegate medical judgment to an algorithm (Akin Gump, 2025).

10. Conclusion

Artificial intelligence has evolved from an experimental technology to a clinically validated and increasingly indispensable tool for the early detection of cancer through medical imaging. Deep learning architectures ranging from well-established U-Net-based CNNs to attention-driven Vision Transformers and hybrid models consistently demonstrate high diagnostic accuracy, frequently surpassing or matching experienced radiologists in controlled studies and prospective trials. Especially notable are the improvements in screening sensitivity (breast cancer), risk-stratified prediction without clinical variables (lung cancer), reduction of inter-reader variability (prostate MRI), and detection in challenging scenarios (pancreatic cancer on non-contrast CT). The integration of multi-modal data fusion, radiogenomics, and generative diffusion models, foundation models, and privacy-preserving federated learning is enabling more biologically comprehensive, generalizable, and equitable diagnostic systems.

However, successful translation into routine clinical practice requires overcoming several critical barriers: seamless integration into existing radiology workflows without causing alert fatigue, rigorous mitigation of algorithmic bias across diverse populations, clear assignment of medicolegal responsibility, alignment with evolving regulatory frameworks (FDA, EU AI Act), and sustainable reimbursement models. Explainable AI techniques are essential for building clinician trust and facilitating human–AI collaboration rather than replacement.

Looking forward, the most transformative potential lies in moving beyond detection toward truly personalized, predictive, and preventive oncology where AI integrates imaging phenotypes with clinical, genomic, and longitudinal data to forecast disease trajectory, guide treatment selection, and optimize population-level screening strategies. Achieving this vision will require sustained investment in high-quality, diverse datasets, standardized validation protocols, interdisciplinary education, and ethical governance. When responsibly developed and thoughtfully implemented, AI-based diagnostic models have the capacity to substantially reduce cancer mortality by enabling earlier intervention, minimizing unnecessary procedures, and maximizing the effectiveness of limited healthcare resources in the era of precision medicine.

References

Beyer, A. M., Tarima, S., Zhou, Y., Kwarteng, J. L., Yen, T. W. F., Winn, A. N., & Beyer, K. M. M. (2025). Artificial intelligence is transforming cancer care: A review of productivity and creative discovery in clinical oncology. *Cancers*, *17*(11), 588. https://doi.org/10.3390/cancers17110588

Gommers, J., Hernström, V., Josefsson, V., Sartor, H., Schmidt, D., Hjelmgren, A., Larsson, A.-M., Hofvind, S., Andersson, I., Rosso, A., Hagberg, O., & Lång, K. (2026). Interval cancer, sensitivity, and specificity comparing AI-supported mammography screening with standard double reading without AI in the MASAI study: A randomised, controlled, non-inferiority, single-blinded, population-based, screening-accuracy trial. *The Lancet*, *407*(10527), 505–514. ((https://doi.org/10.1016/S0140-6736(25)02464-X))

Kim, E.-K., Kim, H. H., Han, B.-K., Kim, K. H., Han, K., Nam, H., ... Moon, H. J. (2020). Changes in cancer detection and false-positive recall in mammography using artificial intelligence: A retrospective, multireader study. The Lancet Digital Health, 2(10), e523–e534. https://doi.org/10.1016/S2589-7500(20)30003-0

Koutsoubis, N., Waqas, A., Yilmaz, Y., Ramachandran, R. P., Schabath, M. B., & Rasool, G. (2025). Privacy-preserving federated learning and uncertainty quantification in medical imaging. *Radiology: Artificial Intelligence*, *7*(4), e240637. https://doi.org/10.1148/ryai.240637

Ma, J., Yang, F., Yang, R., Li, Y., & Chen, Y. (2025). Interpretable deep learning for gastric cancer detection: A fusion of AI architectures and explainability analysis. *Frontiers in Immunology*, *16*, 1596085. https://doi.org/10.3389/fimmu.2025.1596085

Ng, C. K. C., & Leung, V. W. S. (2025). Editorial: Artificial intelligence in radiology and radiation oncology. *Frontiers in Radiology*, *5*, 1657119. https://doi.org/10.3389/fradi.2025.1657119

Pal, A., Rai, H. M., Yoo, J., Lee, S.-R., & Park, Y. (2025). ViT-DCNN: Vision transformer with deformable CNN model for lung and colon cancer detection. *Cancers*, *17*(18), 3005. https://doi.org/10.3390/cancers17183005

Alis, D., Alis, C., Yildirim, I. O., & Er, A. (2025). Comparison of artificial intelligence and radiologists in MRI-based prostate cancer diagnosis: A meta-analysis of accuracy and effectiveness. Biomedicines, 14(1), Article 20. https://doi.org/10.3390/biomedicines14010020

Sharif, M. I., Mehmood, M., Uddin, M. P., Siddique, K., Akhtar, Z., & Waheed, S. (2024). Federated learning for analysis of medical images: A survey. *Journal of Computer Science*, *20*(12), 1610–1621. https://doi.org/10.3844/jcssp.2024.1610.1621

Huang, J., Xiang, Y., Gan, S., Wu, L., Yan, J., Ye, D., & Zhang, J. (2025). Application of artificial intelligence in medical imaging for tumor diagnosis and treatment: A comprehensive approach. Discovery Oncology, 16(1), Article 1625. https://doi.org/10.1007/s12672-025-03307-3

Takahashi, S., Sakaguchi, Y., Kouno, N., Takasawa, K., Ishizu, K., & Akagi, Y. (2024). Comparison of vision transformers and convolutional neural networks in medical image analysis: A systematic review. Journal of Medical Systems, 48(1), Article 84. https://doi.org/10.1007/s10916-024-02105-8

Yu, K.-H. (2020). Reproducible machine learning methods for lung cancer detection using computed tomography images: Algorithm development and validation. *Journal of Medical Internet Research*, *22*(8), e10017. https://doi.org/10.2196/10017

Yuan, W., Chen, Y., Zhu, B., Yang, S., Zhang, J., Mao, N., Xiang, J., ... Madabhushi, A. (2025). Pancancer outcome prediction via a unified weakly supervised deep learning model. Signal Transduction and Targeted Therapy, 10(1), Article 285. https://doi.org/10.1038/s41392-025-02374-w

Zhang, Z., Yao, L., Wang, B., Jha, D., Durak, G., & Keles, E. (2025). DiffBoost: Enhancing medical image segmentation via text-guided diffusion models. *PMC12573213*. https://doi.org/10.1101/2025.07.12.25331423

Zou, Y., & Miao, P. (2025). Explainable AI-enabled hybrid deep learning architecture for breast cancer detection. *Frontiers in Immunology*, *16*, 1658741. https://doi.org/10.3389/fimmu.2025.1658741

Khan, A., Sohail, A., Zahoora, U., & Qureshi, A. S. (2020). A survey of the recent architectures of deep convolutional neural networks. Artificial intelligence review, 53(8), 5455-5516.

Khunte, M., Chae, A., Wang, R., Jain, R., Sun, Y., Sollee, J. R., ... & Bai, H. X. (2023). Trends in clinical validation and usage of US Food and Drug Administration-cleared artificial intelligence algorithms for medical imaging. Clinical Radiology, 78(2), 123-129.

Harvey, H. B., & Gowda, V. (2020). How the FDA regulates AI. Academic radiology, 27(1), 58-61.

Potnis, K. C., Ross, J. S., Aneja, S., Gross, C. P., & Richman, I. B. (2022). Artificial intelligence in breast cancer screening: evaluation of FDA device regulation and future recommendations. JAMA internal medicine, 182(12), 1306-1312.

Milam, M. E., & Koo, C. W. (2023). The current status and future of FDA-approved artificial intelligence tools in chest radiology in the United States. Clinical Radiology, 78(2), 115-122.

Dixit, S., Kumar, A., & Srinivasan, K. (2023). A current review of machine learning and deep learning models in oral cancer diagnosis: recent technologies, open challenges, and future research directions. Diagnostics, 13(7), 1353.

Benning, L., Peintner, A., & Peintner, L. (2022). Advances in and the applicability of machine learning-based screening and early detection approaches for cancer: A primer. Cancers, 14(3), 623.

Martinez, R. G., & van Dongen, D. M. (2023). Deep learning algorithms for the early detection of breast cancer: A comparative study with traditional machine learning. Informatics in Medicine Unlocked, 41, 101317.

Neha, F., Bhati, D., Shukla, D. K., Dalvi, S. M., Mantzou, N., & Shubbar, S. (2024). U-net in medical image segmentation: A review of its applications across modalities. arXiv preprint arXiv:2412.02242.

Azad, R., Aghdam, E. K., Rauland, A., Jia, Y., Avval, A. H., Bozorgpour, A., ... & Merhof, D. (2024). Medical image segmentation review: The success of u-net. IEEE Transactions on Pattern Analysis and Machine Intelligence.

Shi, C., Su, Z., Zhang, K., Xie, X., Zheng, X., Lu, Q., & Yang, J. (2024). CloudFU-Net: A fine-grained segmentation method for ground-based cloud images based on an improved encoder–decoder structure. IEEE Transactions on Geoscience and Remote Sensing, 62, 1-13.

Wong, Y. M., Yeap, P. L., Ong, A. L. K., Tuan, J. K. L., Lew, W. S., Lee, J. C. L., & Tan, H. Q. (2024). Machine learning prediction of dice similarity coefficient for validation of deformable image registration. Intelligence-Based Medicine, 10, 100163.

Taciuc, I. A., Dumitru, M., Marinescu, A., Serboiu, C., Musat, G., Gherghe, M., ... & Vrinceanu, D. (2025). Enhancing Malignant Lymph Node Detection in Ultrasound Imaging: A Comparison Between the Artificial Intelligence Accuracy, Dice Similarity Coefficient and Intersection over Union. Journal of Mind and Medical Sciences, 12(1), 29.

Younesi, A., Ansari, M., Fazli, M., Ejlali, A., Shafique, M., & Henkel, J. (2024). A comprehensive survey of convolutions in deep learning: Applications, challenges, and future trends. IEEE Access, 12, 41180-41218.

Zhong, X., Lu, G., & Li, H. (2025). Vision Mamba and xLSTM-UNet for medical image segmentation. Scientific reports, 15(1), 8163.

Li, X., Li, M., Yan, P., Li, G., Jiang, Y., Luo, H., & Yin, S. (2023). Deep learning attention mechanism in medical image analysis: Basics and beyonds. International Journal of Network Dynamics and Intelligence, 93-116.

Habib, G., Malik, I. A., Qureshi, S., Ra, I. H., Singh, S., & Sharma, S. (2024). Harnessing the power of attention for patch-based biomedical image classification. IEEE Access.

Sarkar, P., Mehtani, A., Gandhi, H. C., Bhalla, J. S., & Tapariya, S. (2022). Paraneoplastic ocular syndrome: a pandora's box of underlying malignancies. Eye, 36(7), 1355-1367.

Alomar, K., Aysel, H. I., & Cai, X. (2025). CNNs, RNNs and Transformers in human action recognition: a survey and a hybrid model. Artificial Intelligence Review, 58(12), 1-44.

Pfeiffer, M., Riediger, C., Leger, S., Kühn, J. P., Seppelt, D., Hoffmann, R. T., ... & Speidel, S. (2020, September). Non-rigid volume to surface registration using a data-driven biomechanical model. In International Conference on Medical Image Computing and Computer-Assisted Intervention (pp. 724-734). Cham: Springer International Publishing.

Zheng, Z., Cao, W., He, Z., & Luo, Y. (2021). Progressive anatomically constrained deep neural network for 3D deformable medical image registration. Neurocomputing, 465, 417-427.

Vincenzo, M. D. (2024). Review on multi-modal AI models to integrate imaging and omics data (Master's thesis).

Simon, B. D., Ozyoruk, K. B., Gelikman, D. G., Harmon, S. A., & Türkbey, B. (2025). The future of multimodal artificial intelligence models for integrating imaging and clinical metadata: a narrative review. Diagnostic and Interventional Radiology, 31(4), 303.

Nam, Y., Kim, J., Jung, S. H., Woerner, J., Suh, E. H., Lee, D. G., ... & Kim, D. (2024). Harnessing artificial intelligence in multimodal omics data integration: paving the path for the next frontier in precision medicine. Annual review of biomedical data science, 7.

Joshi, G., Walambe, R., & Kotecha, K. (2021). A review on explainability in multimodal deep neural nets. IEEE Access, 9, 59800-59821.

Messiou, C., Lee, R., & Salto-Tellez, M. (2023). Multimodal analysis and the oncology patient: Creating a hospital system for integrated diagnostics and discovery. Computational and Structural Biotechnology Journal, 21, 4536-4539.

Ayantayo, A., Kaur, A., Kour, A., Schmoor, X., Shah, F., Vickers, I., ... & Abdelsamea, M. M. (2023). Network intrusion detection using feature fusion with deep learning. Journal of Big Data, 10(1), 167.

Lo Gullo, R., Daimiel, I., Morris, E. A., & Pinker, K. (2020). Combining molecular and imaging metrics in cancer: radiogenomics. Insights into imaging, 11(1), 1.

Fathi Kazerooni, A., Bakas, S., Saligheh Rad, H., & Davatzikos, C. (2020). Imaging signatures of glioblastoma molecular characteristics: a radiogenomics review. Journal of Magnetic Resonance Imaging, 52(1), 54-69.

Ayus, I., & Jena, B. (2025). Machine and deep learning-based methods for genotype O (6)-methylguanine-DNA-methyltransferase status prediction. In Radiomics and Radiogenomics in Neuro-Oncology (pp. 35-47). Academic Press.

Saxena, S., Agrawal, A., Dash, P., Jena, B., Khanna, N. N., Paul, S., ... & Suri, J. S. (2023). Prediction of O-6-methylguanine-DNA methyltransferase and overall survival of the patients suffering from glioblastoma using MRI-based hybrid radiomics signatures in machine and deep learning framework. Neural computing and applications, 35(18), 13647-13663.

Hernström, V., Josefsson, V., Sartor, H., Schmidt, D., Larsson, A. M., Hofvind, S., ... & Lång, K. (2025). Screening performance and characteristics of breast cancer detected in the Mammography Screening with Artificial Intelligence trial (MASAI): a randomised, controlled, parallel-group, non-inferiority, single-blinded, screening accuracy study. The Lancet Digital Health, 7(3), e175-e183.

Pesapane, F., Nicosia, L., D'Amelio, L., Quercioli, G., Pannarale, M. R., Priolo, F., ... & Cassano, E. (2025). Artificial Intelligence-Driven Personalization in Breast Cancer Screening: From Population Models to Individualized Protocols. Cancers, 17(17), 2901.

Cellina, M., Cacioppa, L. M., Ce, M., Chiarpenello, V., Costa, M., Vincenzo, Z., ... & Floridi, C. (2023). Artificial intelligence in lung cancer screening: the future is now. Cancers, 15(17), 4344.

Arshad, M. F., Chowdhury, A. T., Sharif, Z., Islam, M. S. B., Sumon, M. S. I., Mohammedkasim, A., ... & Pedersen, S. (2025). Artificial Intelligence and Machine Learning in Lung Cancer: Advances in Imaging, Detection, and Prognosis. Cancers, 17(24), 3985.

Cai, G., Cai, Y., Zhang, Z., Cao, Y., Wu, L., Ergu, D., ... & Zhao, Y. (2024). Medical ai for early detection of lung cancer: A survey. arXiv preprint arXiv:2410.14769.

Pierre, C. C. (2024). Contextualizing Race and Ethnicity in the Practice of Laboratory Medicine. Clinics in Laboratory Medicine, 44(4), 591-605.

Quinn, L., Tryposkiadis, K., Deeks, J., De Vet, H. C., Mallett, S., Mokkink, L. B., ... & Sitch, A. (2023). Interobserver variability studies in diagnostic imaging: a methodological systematic review. The British Journal of Radiology, 96(1148), 20220972.

Lappas, G., Staut, N., Lieuwes, N. G., Biemans, R., Wolfs, C. J., van Hoof, S. J., ... & Verhaegen, F. (2022). Inter-observer variability of organ contouring for preclinical studies with cone beam Computed Tomography imaging. Physics and Imaging in Radiation Oncology, 21, 11-17.

Tarhini, A. A., Dave, P., & El Naqa, I. (2025). General artificial intelligence for the diagnosis and treatment of cancer: the rise of foundation models. BJR| Artificial Intelligence, 2(1), ubaf015.

Bengesi, S., El-Sayed, H., Sarker, M. K., Houkpati, Y., Irungu, J., & Oladunni, T. (2024). Advancements in generative AI: A comprehensive review of GANs, GPT, autoencoders, diffusion model, and transformers. IEEe Access, 12, 69812-69837.

Hadiyya, K., Dina, R., & Mokhtar, B. (2025). Diffusion Models in Generative AI: Principles, Applications, and Future Directions.

Kidder, B. L. (2024). Advanced image generation for cancer using diffusion models. Biology Methods and Protocols, 9(1), bpae062.

Osorio, P., Jimenez-Perez, G., Montalt-Tordera, J., Hooge, J., Duran-Ballester, G., Singh, S., ... & Mohammadi, S. (2024). Latent diffusion models with image-derived annotations for enhanced ai-assisted cancer diagnosis in histopathology. Diagnostics, 14(13), 1442.

Hosseini, A., & Serag, A. (2025). Is synthetic data generation effective in maintaining clinical biomarkers? Investigating diffusion models across diverse imaging modalities. Frontiers in Artificial Intelligence, 7, 1454441.

Sufian, M. A., Alsadder, L., Hamzi, W., Zaman, S., Sagar, A. S., & Hamzi, B. (2024). Mitigating Algorithmic Bias in AI-Driven Cardiovascular Imaging for Fairer Diagnostics. Diagnostics, 14(23), 2675.

Mottez, C., Fay, L., Varma, M., Ostmeier, S., & Langlotz, C. (2025). From Detection to Mitigation: Addressing Bias in Deep Learning Models for Chest X-Ray Diagnosis. In Biocomputing 2026: Proceedings of the Pacific Symposium (pp. 538-550).

Jiao, Z., Choi, J. W., Halsey, K., Tran, T. M. L., Hsieh, B., Wang, D., ... & Bai, H. X. (2021). Prognostication of patients with COVID-19 using artificial intelligence based on chest x-rays and clinical data: a retrospective study. The Lancet Digital Health, 3(5), e286-e294.

Fang, H., Qiu, Y., Yu, H., Yu, W., Kong, J., Chong, B., ... & Xu, K. (2024). Privacy leakage on dnns: A survey of model inversion attacks and defenses. arXiv preprint arXiv:2402.04013.

Hassija, V., Chamola, V., Mahapatra, A., Singal, A., Goel, D., Huang, K., ... & Hussain, A. (2024). Interpreting black-box models: a review on explainable artificial intelligence. Cognitive Computation, 16(1), 45-74.

Gadzicki, K., Khamsehashari, R., & Zetzsche, C. (2020, July). Early vs late fusion in multimodal convolutional neural networks. In 2020 IEEE 23rd international conference on information fusion (FUSION) (pp. 1-6). IEEE.

AI Centre for Value Based Healthcare. (2025, December 9). *AI Centre team presents advances in federated learning, oncology data extraction, and population health at ISPOR Europe 2025*. https://www.aicentre.co.uk/news-and-events/news/ai-centre-team-presents-advances-in-federated-learning-oncology-data-extraction-and-population-health-at-ispor-europe-2025

Akin Gump Strauss Hauer & Feld LLP. (2025, December 11). *Artificial intelligence in clinical decision-making: Regulatory roadmap and reimbursement strategies*. https://www.akingump.com/en/insights/alerts/artificial-intelligence-in-clinical-decision-making-regulatory-roadmap-and-reimbursement-strategies

Mayfield, W., Pasquinelli, M., & Fintelmann, F. (2026, January 7). AI tools like Sybil poised to improve lung cancer screening, risk prediction. *CHEST Physician*. https://www.chestphysician.org/ai-tools-like-sybil-poised-to-improve-lung-cancer-screening-risk-prediction/

MedTech Dive. (2026, February 2). *FDA fields record number of AI device submissions in 2025*. https://www.medtechdive.com/news/ai-medtech-track-new-devices-fda/748397/