ACCSCIENCE PUBLISHING

Eurasian Journal of Medicine and Oncology

REVIEW ARTICLE

Advances in image processing and pattern recognition in cancer detection, prediction, diagnosis, and prognosis

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Citation: Sah AK, Choudhary RK, Elshaikh EH, *et al*. Advances in image processing and pattern recognition in cancer detection, prediction, diagnosis, and prognosis. *Eurasian J Med Oncol*. 2026;10(4):025220226. doi: 10.36922/EJMO025220226

Received: May 29, 2025

Revised: November 2, 2025

Accepted: November 14, 2025

Published online: July 1, 2026

Abstract

Cancer remains a global health issue, with early detection, correct diagnosis, and exact prognosis playing critical roles in improving patient outcomes. Recent developments in image processing and pattern recognition have significantly enhanced cancer detection, prediction, diagnosis, and prognosis, bridging the gap between conventional radiological methods and state-of-the-art artificial intelligence (AI)-based analytics. This review provides an in-depth introduction to the concepts, methods, and practical applications of image processing and pattern recognition in oncology. Image preprocessing algorithms, tumor segmentation algorithms, feature extraction, and pattern recognition methods based on AI, such as machine learning and deep learning models (e.g., convolutional neural networks, recurrent neural networks, and transformers), are all significant areas. We reviewed cancer prediction using radiomics, radiogenomics, AI-based histopathological diagnosis, and multimodal data fusion from imaging, genomics, and clinical history for personalized prognosis. The impact of explainable AI, 3D/4D imaging, nanotechnology-facilitated imaging, and cloud-based AI solutions is also discussed, including its impact on precision oncology and remote diagnosis. Even with these developments, significant clinical use limitations remain, including limited annotated datasets, poor interpretability, ethical considerations, and regulatory issues. This review focuses on emerging trends, including federated learning, quantum computing, and real-time AI applications, that could revolutionize cancer imaging and management. Image processing and pattern recognition, if integrated with interdisciplinary research, have the potential to develop more precise, equitable, and egalitarian cancer care in the future.

Keywords: Cancer imaging; Pattern recognition; Tumor classification; Artificial intelligence in cancer diagnosis; Multimodal data integration

1. Introduction

Cancer remains a major global health challenge, accounting for approximately 10 million deaths annually, according to the World Health Organization.[1] Its complexity stems from its heterogeneity, which manifests in various forms, progresses at different rates, and responds variably to treatment. Despite therapeutic advances, patient survival is still heavily dependent on the stage at which cancer is detected. Early and accurate diagnosis enhances treatment efficacy, reduces healthcare costs, and improves survival outcomes. Traditional imaging modalities such as X-rays, computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and ultrasound have long been integral to cancer detection, staging, and monitoring. However, these techniques depend heavily on subjective interpretation by radiologists, which introduces variability and potential diagnostic error.[2,3] Recent advances in artificial intelligence (AI), particularly machine learning and deep learning, have transformed oncology imaging by enabling faster, more accurate, and reproducible analyses. AI-driven tools now automate tasks such as tumor segmentation, lesion classification, and prognosis estimation, with convolutional neural networks (CNNs) showing strong performance in differentiating benign from malignant tumors and predicting outcomes from imaging features.[4]

Image processing and pattern recognition techniques underpin these advances. Image processing enhances image quality through segmentation, contrast adjustment, and feature extraction, while pattern recognition enables the identification of meaningful biomarkers and structural patterns that support classification and clinical decision-making.[5] Radiomics, for example, quantifies imaging features that correlate with tumor biology, aiding diagnosis and treatment stratification. Similarly, AI-powered histopathologic image analysis has improved the consistency and precision of cancer classification and grading, reducing interobserver variability.[6]

Humanity is experiencing a major technological shift, with AI transforming fields once dependent on human cognition. Advances in neural networks, especially CNNs and graphics processing unit (GPU) technology, have revolutionized image analysis by improving accuracy and efficiency. AI enhances pattern recognition and classification, boosting diagnostic precision across modalities such as CT and MRI. Current AI products mainly focus on neuroimaging, chest imaging, and high-prevalence diseases such as lung cancer, stroke, and breast cancer, reflecting their clinical importance. Most are certified under the Medical Devices Directive (MDD) or Neducak Device Regulation (MDR) Class I/IIa, indicating moderate-risk compliance. A surge in AI product development between 2017 and 2020 has since stabilized. The key developments in AI-based imaging, emphasizing CNN-driven innovation, regulatory challenges, and the evolving impact of AI on diagnostic practice and workforce dynamics.[7]

Importantly, detection, diagnosis, prediction, and prognosis in oncology are interconnected stages that benefit collectively from computational imaging advancements. Screening tools such as mammography, low-dose CT, and colonoscopy support early detection. AI-enhanced algorithms integrate imaging, genomic, and clinical data to predict individual cancer risk, enabling proactive interventions. Diagnostic tools now assess tumor type, stage, and molecular characteristics more precisely, guiding personalized therapies. Prognostic models leveraging radiomics and deep learning predict disease recurrence and progression based on imaging-derived features, such as heterogeneity and vascularity.[8,9] Dankwa-Mullan *et al.*[10] highlighted major AI advances, such as deep learning for cancer diagnosis and predictive analytics for personalized treatment, thereby improving the precision of care. However, biased training data and limited access in low-income and rural areas raise concerns about equity. To ensure AI benefits all populations, future work must emphasize inclusive datasets, consider social determinants of health, and establish ethical frameworks. Addressing these gaps is vital for AI to promote cancer health equity and guide future research and policy.

Artificial intelligence is transforming pathology and oncology by improving cancer diagnosis, prognosis, and treatment planning. Through a systematic review, the European Society for Medical Oncology (ESMO) Precision Oncology Working Group and international experts analyzed studies applying AI algorithms to tumor diagnosis, molecular biomarker detection, and prognostic assessment. The findings show that AI integration in digital pathology enhances image analysis accuracy and efficiency, enabling automated tumor detection, classification, and prediction of treatment response and patient outcomes. Despite these advances, challenges such as limited data availability, algorithm transparency, and regulatory barriers persist. Currently, no AI-based prognostic or predictive biomarkers are supported by level IA or IB evidence. However, emerging approaches, including foundation models, generalist systems, and transformer-based deep learning, hold strong potential to drive future progress in cancer research. AI is also facilitating the integration of multi-omics data, enabling improved patient stratification and personalized therapy design. Overall, AI is expected to substantially enhance the precision and efficiency of cancer diagnosis and management. Addressing existing technical, ethical, and regulatory challenges will be critical to its broader clinical adoption and to realizing its full potential in advancing precision oncology and improving patient outcomes.[11]

This review highlights the critical role of image processing and pattern recognition in revolutionizing cancer care. While traditional diagnostic methods remain valuable, they are often limited in sensitivity and specificity, especially at early stages. Emerging AI techniques, including computer-aided detection (CAD), radiogenomics, and explainable AI (XAI), enhance diagnostic precision, automate complex image interpretation, and support clinical decisions with greater reliability. Furthermore, pattern recognition models detect subtle cues overlooked by human observers, enabling more accurate predictions of disease behavior and treatment response.

By fostering interdisciplinary collaboration among oncologists, data scientists, and engineers, these technologies hold promise for transforming cancer detection, diagnosis, and management. This review synthesizes recent advances and identifies future directions to guide innovative, data-driven oncology practices that ultimately improve patient outcomes worldwide.

2. Fundamentals of image processing in oncology

Image processing is of paramount importance in modern oncology because it is capable of improving the quality of medical images, yielding valuable information, and facilitating computer-aided tumor diagnosis, classification, and prediction. Advanced computational algorithms used together with imaging modalities such as MRI, CT, PET, and ultrasound have greatly improved cancer diagnosis and treatment planning. Building blocks of image processing in cancer, including preprocessing, segmentation, feature extraction, and registration, are discussed here (Figure 1 and Table 1).[12]

Table 1. Techniques in image processing for cancer detection

Approach	Example (algorithm/model)	Cancer type(s)	Dataset(s) used	Performance (accuracy/AUC/sensitivity)	Reference
Radiomics	SVM + handcrafted features	Lung, head, & neck	NSCLC-radiomics, TCIA	AUC: 0.79–0.85 (survival prediction)	13–17
Radiomics + ML	Random forest + LASSO/RFE	Breast & prostate	TCGA (breast MRI), private hospital cohorts (prostate mpMRI)	Accuracy: 80–97%; AUC: 0.75–0.80 (breast); 97% (prostate Gleason classification)	18-19
DL	ResNet-50 CNN	Breast, lung	BreakHis (breast histopathology); LIDC-IDRI (lung CT)	Breast: Accuracy: ≈ 90.2%, AUC: ≈ 90.0% (IDC detection); Lung: Accuracy: ≈ 88.4% (nodule detection)	20–24
Hybrid (radiomics + DL)	CNN + radiomic fusion	Glioblastoma	BraTS	AUC: 0.89–0.94 (tumor subtype classification)	25–27

Abbreviations: AUC: Area under the curve; BraTS: Brain Tumor Segmentation; CNN: Convolutional neural network; CT: Computed tomography; DL: Deep learning; IDC: Invasive ductal carcinoma; LASSO: Least absolute shrinkage and selection operator; LIDC-IDRI: Lung Image Database Consortium and Image Database Resource Initiative; ML: Machine learning; MRI: Magnetic resonance imaging; NSCLC: Non-small cell lung cancer; RFE: Recursive feature elimination; SVM: Support vector machine; TCGA: The Cancer Genome Atlas; TCIA: The Cancer Imaging Archive.

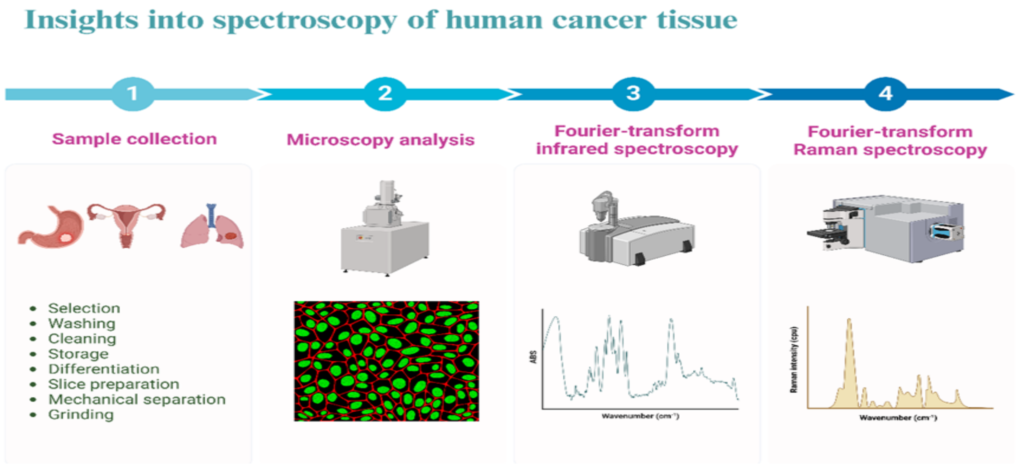

Figure 1. Steps in the imaging process for cancer tissue diagnosis and prognosis

2.1. Image preprocessing methods: Noise reduction, artifact elimination, and normalization

Medical image preprocessing is a critical first step in oncology image analysis, as raw images are often affected by noise, artifacts, and variability caused by patient motion, hardware limitations, or differences across imaging modalities. The goal of preprocessing is to improve image quality and ensure accurate, reproducible analysis in downstream tasks such as tumor detection, segmentation, and feature extraction. Noise reduction techniques, including Gaussian filtering, median filtering, and wavelet-based denoising, effectively suppress random intensity fluctuations while preserving important anatomical structures, thus enhancing image clarity.[28] Artifact correction methods address distortions introduced by motion, metal implants, or scanner defects; common solutions include bias field correction and inpainting, which help maintain the anatomical fidelity of the image. Intensity normalization ensures consistency across scans and subjects, particularly in multi-center studies. Techniques such as histogram equalization and intensity standardization are widely used to harmonize brightness and contrast levels between images.[29] These preprocessing methods form the backbone of CAD systems, radiomics, and AI-enabled oncology models. By improving signal-to-noise ratio and harmonizing imaging data across populations and platforms, preprocessing significantly enhances tumor localization, staging, and the reproducibility of imaging biomarkers used in clinical decision-making.

2.2. Segmentation of anatomical structures and tumors

Segmentation is a critical component of medical image processing, enabling the accurate delineation of anatomical structures and pathological regions, particularly tumors. It involves dividing medical images into meaningful regions to distinguish normal tissue from the area of interest. Accurate segmentation allows for the precise quantification of tumor volume, shape, and texture, essential parameters for diagnosis, staging, radiotherapy planning, and treatment monitoring. Conventional segmentation techniques include thresholding, region growing, and clustering. Thresholding methods, both global and adaptive, segment structures based on intensity differences and are often used to isolate tumor regions from background tissue.[12] Region growing starts from user-defined seed points and expands to neighboring pixels based on predefined similarity criteria, effectively capturing homogeneous tumor areas. Clustering techniques such as k-means and fuzzy c-means group pixels with similar intensity values, making them useful for segmenting tumors with heterogeneous or complex intensity distributions.[30]

To address the limitations of traditional approaches, more advanced methods have been introduced. Active contour models (snakes) evolve image boundaries by minimizing an energy function related to the object's edge and internal smoothness constraints. Graph cuts frame segmentation as a global optimization problem and provide robust boundary delineation, particularly in complex anatomical settings.[31] The most significant advancement in recent years has been the introduction of deep learning-based segmentation methods. Architectures such as U-Net and V-Net leverage encoder–decoder networks to capture both local and global spatial features, making them highly effective for segmenting tumors in radiological and histopathological images. These models have demonstrated high accuracy and robustness, achieving Dice similarity coefficients exceeding 0.85 across various cancers, including gliomas and lung malignancies.[32–34] By automating and refining the segmentation process, especially through deep learning, interobserver variability is minimized, and the precision of image-guided interventions, such as radiotherapy, is significantly enhanced.

2.3. Feature extraction: Texture, shape, intensity, and higher-order features

Feature extraction is a pivotal step in oncologic image processing, as it transforms complex image data into quantitative descriptors that facilitate tumor characterization, diagnosis, and prognosis prediction. These features, often referred to as imaging biomarkers or radiomics features, capture critical information about tumor heterogeneity, shape, texture, and intensity. Texture features, such as those derived from the gray-level co-occurrence matrix and local binary patterns, quantify spatial variations in pixel intensity and help differentiate malignant tumors from benign ones based on tissue microarchitecture.[35] Intensity-based features, including the mean, median, and standard deviation of pixel values, reflect underlying tissue density and metabolic activity and are particularly valuable in PET and MRI. Morphological features, such as tumor size, roundness, compactness, and border irregularity, provide insight into tumor aggressiveness and are essential for staging and treatment planning. Beyond first-order descriptors, radiomics incorporates higher-order features combining shape, intensity, and texture into multivariate models used for outcome prediction and therapy assessment. These features are fed into machine learning algorithms to classify tumor subtypes, estimate recurrence risk, and guide personalized therapy strategies. Several radiomics-based predictive models have demonstrated robust diagnostic and prognostic performance, achieving area under the curve (AUC) values exceeding 0.90 for tasks such as tumor grading, recurrence prediction, and treatment response evaluation.[36-37]

Additionally, studies have established strong correlations between extracted radiomic features and specific molecular or genetic profiles. For example, radiomic signatures derived from MRI and CT imaging have shown high predictive value for identifying *IDH* mutation status in gliomas, linking imaging phenotypes with genomic alterations.[38-39] Such integration of imaging and molecular data advances the potential of noninvasive precision oncology.

2.4. Image registration: Aligning multimodal images for comprehensive analysis

Image registration is a fundamental technique in oncologic image processing that enables the alignment of images acquired from different modalities (e.g., CT, MRI, PET) or at different time points, thus facilitating comprehensive analysis and longitudinal studies. By accurately mapping corresponding anatomical structures, registration improves tumor localization, treatment planning, and disease monitoring. Depending on the complexity of anatomical changes, different registration methods are employed. Rigid registration applies basic transformations such as translation and rotation, preserving spatial relationships, and is commonly used when patient positioning is consistent. Affine registration extends this approach by incorporating scaling and shearing to account for variations in patient placement and anatomical proportion. Non-rigid (or deformable) registration, the most advanced form, accommodates complex tissue deformations caused by physiological motion (e.g., breathing), tumor growth, or organ shifting, ensuring precise alignment of anatomical structures.[31]

Non-rigid registration has demonstrated particular clinical value in aligning functional PET data with structural CT or MRI in cases such as head and neck cancer, improving diagnostic accuracy and facilitating integrated tumor evaluation.[40] This level of precision is essential in adaptive radiotherapy, where accurate tumor margin delineation is necessary to reduce radiation exposure to surrounding healthy tissues.[41]

The clinical utility and diagnostic accuracy of these image processing techniques, including image registration, have been validated across multiple cancer types. For example, in breast cancer, automated mammography enhanced with texture-based radiomics improves sensitivity and specificity in early detection.[39,41] In lung cancer, CT-based radiomics combined with machine learning achieves over 85% accuracy in distinguishing benign from malignant nodules.[42] In brain tumors, particularly gliomas, multiparametric MRI integrated with radiomics and deep learning enables accurate prediction of tumor grade and patient survival, with high AUC values.[43] Together, these core image processing techniques, including preprocessing, segmentation, feature extraction, and registration, are transforming oncology by enabling individualized, data-driven clinical decision-making and improving diagnostic accuracy, treatment precision, and patient outcomes. Advanced radiopharmaceuticals are revolutionizing cancer imaging and therapy by enabling more focused therapies. Targeted alpha therapy utilizes alpha-emitting radionuclides to deliver powerful radiation doses directly to cancer cells, sparing surrounding healthy tissue (Figure 2).[44]

3. Pattern recognition techniques in cancer analysis

Pattern recognition techniques are vital in oncologic imaging, enabling automated tumor detection, classification, and prognostic prediction by analyzing patterns in radiological, histological, and molecular data. These methods, grounded in machine learning and deep learning, enhance diagnostic accuracy and support personalized treatment planning. The integration of classical machine learning models, deep neural networks, and hybrid approaches has significantly advanced cancer image analysis (Figure 3 and Table 2).

Classical machine learning algorithms remain widely used due to their ability to handle structured data and engineered features. For example, support vector machines (SVMs) are effective in distinguishing between benign and malignant tumors by identifying optimal separating hyperplanes, with kernel-based SVMs offering improved accuracy through nonlinear feature mapping.[58] The k-nearest neighbor algorithms classify tumor types based on similarity to labeled instances, while random forest algorithms enhance robustness by combining predictions from multiple decision trees, reducing overfitting and improving interpretability.[59] Despite their utility, these classical approaches rely on manual feature extraction, limiting scalability to high-dimensional image data.

Table 2. Pattern recognition algorithms in cancer diagnosis

Algorithm	Description	Applications in cancer diagnosis	Advantages	Reference
Support vector machines (SVM)	A supervised learning algorithm for classification and regression.	Identifying cancer types from histopathological images.	High accuracy, effective in high-dimensional spaces.	45–49
Artificial neural networks (ANNs)	Computational models inspired by biological neural networks, capable of pattern recognition	Classification of mammogram images for breast cancer.	Can learn complex patterns, adaptive.	49–52
Convolutional neural networks (CNNs)	A deep learning algorithm is primarily used for image processing, especially in medical imaging.	Tumor detection in medical images (e.g., computed tomography, magnetic resonance imaging).	Highly effective in image classification and detection.	47,53–56
Random forests	Ensemble learning method for classification, using multiple decision trees.	Classifying cancerous vs non-cancerous tissues.	Robust, handles large datasets well.	50,57
K-nearest neighbors (KNN)	A non-parametric classification algorithm that classifies based on the closest feature matches.	Cancerous tissue identification in biopsies.	Simple, interpretable, and effective in smaller datasets.	51

Deep learning has transformed cancer imaging by enabling automatic, end-to-end feature learning. CNNs such as AlexNet, Visual Geometry Group (VGG), ResNet, and EfficientNet extract hierarchical image features without explicit engineering, achieving high accuracy in tumor detection and grading across modalities such as MRI, CT, PET, and histopathology.[60] Architectures such as U-Net and Mask Region-Based CNN are extensively used for tumor segmentation and lesion localization due to their ability to capture spatial details and contextual information.

For temporal and sequential data analysis, recurrent neural networks, including long short-term memory and gated recurrent unit models, are applied in longitudinal cancer imaging studies to monitor tumor progression over time. These networks effectively model time-series data such as dynamic contrast-enhanced MRI. Transformers, which excel at capturing long-range dependencies and multimodal integration, have also been employed to analyze sequential imaging data alongside genomic or clinical inputs, advancing holistic cancer modeling.[61]

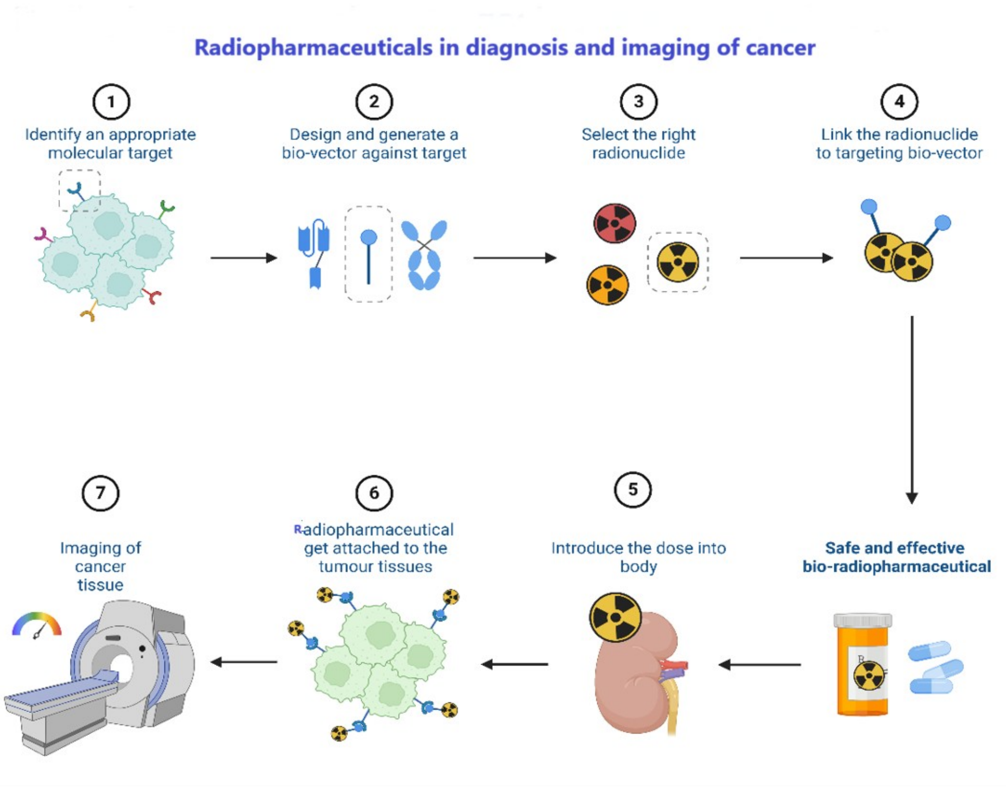

Figure 2. Radiopharmaceuticals technique in cancer imaging

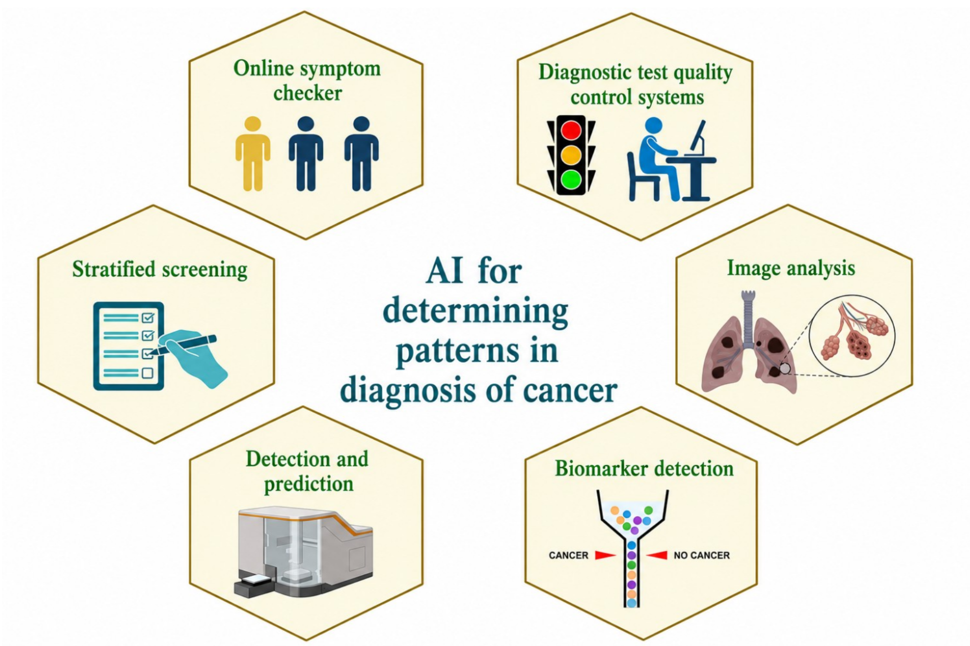

Figure 3. Early diagnosis of cancer using pattern recognition and artificial intelligence (AI)

A persistent challenge in cancer imaging is the scarcity of annotated datasets, as labeling requires significant expertise and time. Transfer learning addresses this limitation by adapting pre-trained models (e.g., ResNet, DenseNet, Inception) trained on large-scale datasets such as ImageNet for cancer-specific tasks. This approach boosts performance on limited medical datasets and reduces training time and resource demands.[62,63]

Finally, ensemble methods and hybrid frameworks combine the strengths of multiple algorithms to improve resilience, accuracy, and generalization. Techniques such as bagging, boosting, and stacking aggregate predictions from diverse models, while hybrid architectures integrating CNNs with machine learning classifiers such as SVM or random forest, enhance performance on small datasets. More comprehensive models that incorporate radiomics, genomics, deep learning, and clinical data provide a multidimensional view of cancer, promoting precision diagnosis and personalized treatment strategies.[64]

4. Applications in cancer detection

The integration of AI and image processing techniques into oncology has revolutionized cancer detection, offering significant improvements in diagnostic accuracy, early intervention, and clinical decision-making. AI-powered tools, including computer-aided screening systems, radiomic biomarker analysis, and second-opinion diagnostic support, have minimized human error, increased workflow efficiency, and enabled earlier identification of malignancies. These advancements are particularly impactful in population-based screening programs for breast, lung, and colorectal cancers, where early detection directly correlates with improved survival outcomes (Table 3).[65]

Table 3. Advances in image processing and pattern recognition for cancer

Technique	Application	Advantages	Challenges	Reference
Survival analysis models	Predicting patient outcomes from imaging	Integrates imaging data with clinical variables; improves prognosis accuracy	Requires longitudinal data; complex to implement	66–69
Tumor growth modeling	Simulating tumor progression over time	Helps in understanding disease dynamics; aids in treatment planning	Relies on assumptions; may not account for all biological variables	70–72
Biomarker identification	Linking imaging features to biomarkers	Non-invasive; aids in monitoring treatment response	Limited by imaging resolution; requires validation	73–75
Artificial intelligence-driven prognostic tools	Predicting recurrence and survival rates	Provides personalized prognosis; improves patient management	Ethical concerns; requires integration with clinical workflows	76–78
Multimodal fusion	Combining imaging with genomic data	Enhances prognosis accuracy; provides a holistic view of disease	Data integration challenges; requires advanced computational methods	77,79-81

Machine learning-based screening systems have enhanced early cancer detection by efficiently analyzing large volumes of imaging data with high precision. In breast cancer, deep learning algorithms applied to mammography improve the detection of microcalcifications and subtle soft-tissue masses, thereby increasing both sensitivity and specificity. AI-assisted mammographic screening supports radiologists in identifying abnormalities that might otherwise go unnoticed under visual inspection.[82] Similarly, in lung cancer, AI models analyzing low-dose CT (LDCT) scans facilitate early identification of pulmonary nodules, especially in high-risk populations such as smokers. These systems enable prompt diagnosis and early treatment initiation. In colorectal cancer, AI-enhanced colonoscopy integrates real-time polyp-detection software that improves the identification of precancerous polyps, thus preventing progression to invasive cancer and reducing physician oversight.[83]

Beyond structural analysis, radiomic biomarkers play a key role in early tumor detection by extracting and quantifying imaging features such as texture, intensity, shape, and heterogeneity that are indicative of malignancy. AI-driven radiomic models have demonstrated strong predictive capability in assessing tumor aggressiveness and treatment response across various cancers, including gliomas, prostate cancer, and hepatocellular carcinoma. When radiomic data are integrated with clinical and genomic information, AI can generate personalized risk assessments and guide precision oncology strategies tailored to individual patients.[84,85]

Despite these advancements, diagnostic uncertainty remains a challenge, with false positives potentially leading to overtreatment and false negatives resulting in delayed care. AI-based second-opinion systems address these issues by acting as decision-support tools for radiologists. These systems analyze imaging data, flag suspicious findings, and assign confidence scores, thereby enhancing diagnostic reliability. Moreover, false-positive reduction decreases unnecessary biopsies and patient anxiety, while false-negative reduction ensures occult malignancies are not missed. Importantly, as these models are exposed to more diverse datasets, they continuously improve through adaptive learning, leading to increasingly accurate and robust cancer detection systems over time.[86]

Brain tumors are abnormal growth within brain tissue, encompassing both primary and metastatic lesions. Effective management relies on early detection, accurate staging, and personalized treatment approaches. AI, through advanced data analysis and pattern recognition, is increasingly integrated into neuro-oncology research to enhance diagnostic accuracy, treatment planning, and prognostic assessment. The research applications of AI in brain tumor studies include its roles in imaging analysis, molecular characterization, treatment response prediction, drug discovery, and exploration of the tumor microenvironment. It further examines methodological frameworks, current limitations, and emerging directions in AI-driven brain tumor research, aiming to inform future investigations and promote the development of precision oncology.[87]

5. Applications in cancer prediction

Artificial intelligence-based predictive models are increasingly vital in identifying individuals at high risk of developing cancer. These models analyze comprehensive data, including demographic, lifestyle, genetic, and imaging parameters, to detect subtle patterns associated with disease predisposition. Machine learning techniques such as SVMs and deep neural networks can process vast historical datasets to identify early indicators of precancerous conditions.[88] For example, in lung cancer, AI-driven risk prediction tools analyze LDCT scans to detect early-stage nodular abnormalities and stratify patients by cancer risk. Similarly, in breast cancer, AI models evaluate mammographic density and parenchymal texture to estimate individualized risk, enabling preventive interventions such as lifestyle modifications or personalized screening strategies at earlier stages of life.[89]

A particularly promising area is radiogenomics, which merges imaging-derived radiomic features with underlying genomic data to improve risk prediction and tumor characterization. AI algorithms extract features such as tumor texture, shape, and heterogeneity from imaging modalities and correlate them with specific genetic mutations. This noninvasive approach provides insight into tumor biology, aggressiveness, and potential for progression without the need for invasive biopsies. For example, in glioblastoma, radiogenomic models have linked MRI-based radiomic signatures with *IDH* mutation and *MGMT* promoter methylation status, both of which are critical prognostic and predictive biomarkers.[90] Such integrative models enable clinicians to make more informed decisions about personalized therapy.

Beyond risk prediction, AI-powered imaging analysis has also transformed how therapeutic responses are anticipated in precision oncology. AI models can process pre-treatment imaging, molecular, and clinical variables to forecast patient responses to chemotherapy, radiotherapy, or immunotherapy. In non-small cell lung cancer, radiomic features derived from CT and PET scans have shown predictive value in identifying patients likely to respond to immune checkpoint inhibitors, allowing early tailoring of treatment strategies.[91] Similarly, in breast cancer, AI models utilizing dynamic contrast-enhanced MRI can predict tumor response to neoadjuvant chemotherapy, enabling clinicians to modify therapeutic regimens before significant disease progression occurs.[92] Such predictive insights can improve treatment efficacy, reduce toxicity, and support real-time decision-making in clinical oncology.

6. Applications in cancer diagnosis

Cancer remains a major global health challenge, necessitating innovative strategies for early detection, accurate diagnosis, and personalized treatment. AI has emerged as a transformative force in oncology, offering advanced tools across the cancer care continuum. The current AI applications in cancer diagnosis and therapy emphasize deep learning–based imaging across CT, MRI, PET, ultrasound, and digital pathology for early tumor detection. AI's expanding roles in genomics, biomarker discovery, liquid biopsy, and non-invasive diagnostics are also explored. In treatment, AI supports clinical decision-making, individualized therapy planning, drug discovery, radiation therapy optimization, robotic surgery, and patient management through survival prediction and remote monitoring. Despite remarkable progress, challenges persist, including data privacy, interpretability, and regulatory constraints. Emerging innovations such as federated learning, synthetic biology integration, and quantum-enhanced AI offer promising future directions. AI holds immense potential to revolutionize oncology by enhancing the precision, efficiency, and personalization of cancer diagnostics and treatments.[93]

Artificial intelligence has brought transformative advancements to histopathological imaging, particularly in the differential diagnosis of malignant and benign lesions. Traditional histological diagnosis, which relies on manual slide inspection by pathologists, is inherently subjective, time-consuming, and susceptible to inter-observer variability. AI-powered computational models, particularly CNNs, can process high-resolution whole-slide images to detect cellular abnormalities, classify tumor types, and identify diagnostically relevant morphological patterns. Trained on large annotated datasets, these models enhance diagnostic accuracy, consistency, and efficiency, thereby supporting pathologists in routine workflows.[94]

Artificial intelligence-driven cell classification and tumor grading systems further enhance diagnostic precision by quantifying cellular features, including shape, size, nuclear atypia, and density. These tools automate grading schemes such as the Gleason score for prostate cancer and Nottingham grade for breast cancer. Deep learning algorithms have demonstrated high accuracy in distinguishing normal, precancerous, and malignant cells, helping pathologists make better-informed decisions. Similarly, AI applications in hematopathology, such as analyzing blood smear images, enable early detection and differentiation of leukemia subtypes, which is critical for timely treatment planning.[95]

One of the most promising applications of AI in histopathology is the detection of rare cancer subtypes, which can often be missed due to limited clinical exposure and diagnostic experience. AI systems trained on large, diverse datasets are capable of identifying subtle histological features indicative of rare malignancies, such as angiosarcoma, medullary carcinoma, and neuroendocrine tumors. These tools support precision medicine by ensuring early, accurate diagnosis and appropriate care pathways for patients with uncommon cancers.[96]

Emerging technologies such as augmented reality (AR) are being integrated with AI-based diagnostic platforms to enhance real-time visualization and decision-making. AR software overlays AI-derived information, such as tumor margins or subtype classification, onto live histopathological or radiological images, assisting clinicians during surgical planning, biopsy guidance, and even telepathology consultations. Intraoperative AR applications are also being explored to delineate tumor boundaries in real time, optimizing resection while preserving healthy tissue.[97]

In addition to morphological analysis, quantitative imaging biomarkers derived from AI algorithms are reshaping objective cancer classification. These biomarkers extracted from radiological and histopathological images help predict malignancy, tumor grade, and even genomic alterations. For example, AI can differentiate malignant from benign lung nodules on CT or predict human epidermal growth factor receptor 2 (HER2) status in breast cancer from histological slides. These imaging biomarkers reduce subjectivity and improve diagnostic reproducibility, paving the way for standardized and repeatable oncology diagnostics.[98]

7. Integration with multimodal data

The inherent complexity of cancer necessitates an integrative approach that combines diverse scientific data to enhance diagnosis, prediction, and therapeutic outcomes. The fusion of imaging, genomic, proteomic, and clinical information provides a comprehensive understanding of tumor biology, progression patterns, and patient-specific responses, ultimately enabling personalized treatment strategies and improved patient prognosis.

While conventional cancer diagnostics rely heavily on histopathology, integrating imaging data with molecular profiles offers deeper biological insight. For example, radiogenomics links imaging phenotypes to genetic alterations, allowing prediction of tumor aggressiveness and the identification of actionable therapeutic targets. Similarly, proteomic analyses reveal protein expression patterns and dysregulated signaling pathways critical for tumor characterization. When combined with clinical data encompassing patient demographics, comorbidities, and treatment history, predictive models become more robust, facilitating tailored therapeutic decisions.[99]

Cutting-edge oncology research increasingly depends on multi-omics technologies that integrate multiple layers of biological information, including genomics (e.g., DNA mutations and copy number variations), transcriptomics (messenger RNA expression profiles), proteomics (protein abundance and modifications), and metabolomics (metabolic signatures). This comprehensive data landscape captures tumor heterogeneity and evolutionary dynamics more effectively than any single modality. Leveraging AI to analyze multi-omics datasets has led to the discovery of novel biomarkers for early cancer detection, patient survival prediction, and optimal therapy selection. For example, combining genetic mutation data with radiomic signatures can enhance the prediction of tumor recurrence and therapy resistance. Furthermore, single-cell multi-omics profiling enables the identification of distinct cellular subpopulations within tumors, facilitating the development of highly specific targeted therapies.[100]

Artificial intelligence platforms capable of integrating heterogeneous data types are transforming cancer research and clinical practice. Machine learning models analyze complex, high-dimensional datasets to detect subtle patterns beyond human discernment. Advanced deep learning-based fusion frameworks seamlessly combine imaging, molecular, and clinical data, supporting real-time clinical decision-making with improved diagnostic and prognostic accuracy. For example, AI-powered digital pathology platforms concurrently analyze histopathology images and genomic sequencing data to refine tumor classification and predict patient outcomes. Similarly, AI-enhanced cloud computing infrastructures consolidate patient information from multiple sources, empowering oncologists to make more informed, data-driven treatment decisions.[101]

8. Role of explainable artificial intelligence in cancer imaging

Artificial intelligence has significantly advanced cancer imaging, improving diagnosis, treatment planning, and prognosis prediction. However, a major limitation of many AI models, especially deep learning models, is their "black box" nature: they provide accurate predictions without explaining how those predictions were made. This lack of transparency undermines clinical credibility and hinders broader acceptance in healthcare settings. XAI seeks to bridge this gap by making AI-driven cancer diagnoses interpretable and understandable to clinicians and patients.[102]

Transparency is essential for the clinical integration of AI in oncology. Unlike traditional imaging interpretation, where radiologists justify diagnoses based on visible features and clinical experience, AI models rely on complex mathematical operations over vast datasets, rendering their decision-making opaque. This opacity raises issues related to regulatory approval, legal accountability, and clinician trust. Moreover, explainability is crucial in high-stakes scenarios such as cancer diagnosis, where erroneous AI predictions, such as false positives or negatives, can have severe consequences.[103]

Several techniques have been developed to elucidate AI decision-making in cancer imaging. For example, Gradient-Weighted Class Activation Mapping (Grad-CAM) highlights regions of medical images that most influenced the AI's classification, enabling physicians to verify which tumor or lesion areas were critical for the diagnosis. Shapley Additive Explanations uses game theory to assign relevance scores to input features, quantifying their contribution to the overall prediction. Similarly, Local Interpretable Model-agnostic Explanations builds simpler surrogate models that approximate the behavior of complex AI systems, making local predictions more understandable. Attention maps, commonly employed in deep learning models such as transformers, identify the most influential image or textual regions for a given prediction, assisting radiologists in validating AI-generated conclusions. These transparency tools do not simply present outcomes; they reveal the rationale behind AI decisions, promoting interpretability and trust.[104,105]

Building trust between patients, clinicians, and AI systems is fundamental for successful AI adoption in oncology. Clinicians are more likely to rely on AI-assisted diagnoses when they can review and confirm the reasoning behind AI predictions. Explainability also facilitates clearer communication with patients, as physicians can use visual explanations to discuss diagnostic findings and treatment options. This transparency fosters patient confidence in AI-supported decisions and encourages shared decision-making. Regulatory agencies such as the United States Food and Drug Administration and the European Medicines Agency have also underscored explainability as a key criterion for approving AI-based medical devices, further driving the development of transparent AI models.[106]

9. The impact of 3D and 4D imaging in oncology

The application of 3D and 4D imaging has substantially advanced tumor visualization, follow-up, and therapy planning in oncology. Three-dimensional imaging modalities such as CT and MRI provide high-resolution, volumetric representations of tumors, enabling precise measurement of tumor size, shape, and spatial location. These capabilities critically impact cancer staging and diagnosis. Moreover, 3D imaging facilitates preoperative planning by allowing surgeons to create virtual models of tumors and surrounding tissues, thereby improving surgical precision and minimizing harm to healthy anatomy. In radiation therapy, 3D imaging supports individualized treatment by enabling accurate delivery of radiation doses targeted to the tumor while sparing adjacent normal tissue.[107]

Four-dimensional imaging extends this concept by incorporating the temporal dimension, allowing time-dependent assessment of tumors. This is particularly valuable for monitoring tumors that move with physiological processes, such as lung or abdominal tumors affected by respiration. 4D imaging enables real-time tracking of tumor motion, enhancing the accuracy of radiation therapy, reducing collateral damage to healthy tissue, and permitting adaptive radiotherapy, with dynamic adjustment of radiation doses based on tumor geometry and location changes during treatment.[108]

The integration of AI with 3D and 4D imaging is revolutionizing tumor identification and therapeutic planning. AI algorithms improve tumor detection and segmentation by reducing human error and accelerating image interpretation. Additionally, AI-powered predictive models can learn tumor behavior patterns and forecast responses to various treatments, facilitating personalized therapeutic strategies. Real-time AI-assisted imaging allows continuous monitoring of tumor progression, empowering clinicians to adapt treatment plans promptly and improve patient outcomes. The synergy between AI and advanced imaging modalities enhances the precision, effectiveness, and personalization of cancer therapy, ultimately contributing to better prognosis and quality of life for patients.[109]

10. Role of mobile and cloud-based artificial intelligence solutions

Mobile and cloud-based AI technologies are revolutionizing cancer diagnosis and treatment by making healthcare more efficient, accessible, and equitable. One of the most promising advancements is the ability to perform remote cancer diagnosis through smartphone-based imaging. As smartphones become increasingly powerful, their integrated imaging capabilities, combined with AI software, can analyze diagnostic images, including X-rays, CT scans, and MRIs, directly on the device. This innovation enables timely and accurate assessment of patients in rural or underserved regions, eliminating the need for long-distance travel. Early detection through smartphone-based AI imaging has the potential to identify initial signs of cancer, allowing for earlier interventions and improved patient outcomes.[110]

Cloud-based deep learning further enhances the scalability and reach of cancer care. By storing and processing large volumes of medical imaging data on remote servers, cloud technology provides oncologists and healthcare providers worldwide with on-demand access to diagnostic resources and AI-powered analyses. This facilitates collaboration among medical experts globally, enabling case cross-checking, second opinions, and knowledge sharing. The cloud's capacity to manage big data and apply sophisticated AI algorithms streamlines diagnostic workflows, improving overall healthcare efficiency. Importantly, this technology ensures that patients in regions with limited medical infrastructure can access advanced diagnostic tools and expert evaluations.[111]

In addition, telemedicine platforms integrated with AI-driven virtual consultations are transforming cancer care delivery. AI assists in patient triage, early diagnosis, and analysis of medical histories and symptoms to support oncologists during consultations. Patients can interact with specialists in real time, receive personalized treatment recommendations, and monitor their therapy progress remotely. This combination of telemedicine and AI reduces geographic disparities in healthcare access, promoting more equitable cancer care worldwide. As AI technologies continue to evolve, they hold the promise to significantly optimize cancer diagnosis, treatment accessibility, and clinical outcomes on a global scale.[112]

11. Application of nanotechnology in cancer imaging

Nanotechnology has demonstrated significant value in enhancing cancer imaging, leading to earlier diagnosis, improved accuracy, and better treatment monitoring. One notable application is the development of nanoparticle-based contrast agents used in imaging modalities. Due to their nanoscale size and engineered surface chemistry, these nanoparticles often exhibit unique optical or magnetic properties, enabling them to penetrate tumor tissues more rapidly and selectively than conventional contrast agents. This results in higher-resolution images, allowing for precise visualization of tumors and accurate determination of their size, location, and growth dynamics. Consequently, nanoparticle contrast agents increase imaging sensitivity, facilitating the detection of cancer at earlier, more treatable stages.[113]

A second major application of nanotechnology in cancer imaging is targeted imaging. Nanoparticles can be functionalized with ligands, antibodies, or drugs that specifically bind to tumor-associated markers or receptors, allowing for highly selective tumor localization. This targeted approach minimizes misdiagnosis and reduces unnecessary invasive procedures. Furthermore, targeted nanoparticles enhance sensitivity in identifying minute or occult tumors and enable tracking at cellular and molecular levels. Such capabilities are crucial for detecting tumor heterogeneity, monitoring therapeutic response, and identifying metastatic spread, ultimately contributing to more personalized and effective treatment strategies.[114]

The integration of nanotechnology with AI is expanding the horizons of cancer imaging. Combining the high sensitivity of nanoparticle-enhanced imaging with AI's advanced analytical power enables more accurate and automated diagnostics. AI algorithms can extract complex patterns and relationships from nanoparticle-augmented images that are often imperceptible to human observers. This synergy facilitates faster and more precise tumor detection, automated tumor segmentation, and reliable assessment of tumor progression. Additionally, AI-driven analysis can optimize nanoparticle design to create tailored contrast agents targeting specific cancer types. Together, AI and nanotechnology are revolutionizing cancer imaging by delivering faster, more accurate, and highly personalized diagnostic solutions, ultimately improving treatment outcomes and efficiency.[115]

12. Ethical considera tions and societal implications

The application of AI in cancer imaging raises significant societal and ethical concerns that must be addressed to ensure fair and responsible use. One of the foremost issues is bias and fairness in AI systems. Since AI models are trained on large datasets, any lack of representativeness or imbalance in these datasets can lead to biased outcomes. This bias may cause disparities in cancer diagnosis and treatment, disproportionately affecting underrepresented groups such as minorities and disadvantaged populations, who are often excluded or underrepresented in clinical trials. Consequently, AI-driven imaging systems risk exacerbating existing health inequities. To prevent this, training datasets must be diverse and representative, and AI models require continuous evaluation and recalibration to detect and mitigate biases effectively.[116]

Another critical ethical challenge is the protection of patient confidentiality and data privacy. AI-powered cancer imaging necessitates collecting and processing sensitive personal data, including medical images, clinical history, and genomic information, thereby heightening the risk of unauthorized access, cyberattacks, and misuse. Such breaches can severely compromise patient privacy and undermine trust in healthcare systems. To safeguard patient information, robust encryption methods must be implemented, and strict adherence to data protection regulations such as the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA) is essential. Regular audits and security assessments of AI systems should also be mandatory to maintain data integrity and confidentiality.[117]

To address these concerns comprehensively, policy frameworks and regulatory standards specific to AI use in oncology are imperative. Ethical guidelines must mandate transparency, accountability, and fairness in AI system development and deployment. Regulatory authorities should require rigorous preclinical and clinical validation of AI technologies to ensure accuracy and equity before granting approval for clinical use. Furthermore, ongoing post-market surveillance should be implemented to monitor AI performance continuously. Collaboration among healthcare professionals, data scientists, ethicists, and policymakers is vital to developing patient-centered AI solutions that uphold societal equity. Legal mandates must enforce safe data-sharing protocols that prioritize patient consent and confidentiality. Finally, continuous education and training programs for healthcare providers on the ethical application of AI will foster trust and promote equitable access to AI-driven oncology care for all populations.[118]

13. Popular open-source tools for cancer image analysis

13.1. TensorFlow

TensorFlow, developed by Google, is one of the leading open-source frameworks for machine learning and deep learning applications. It offers a comprehensive ecosystem that supports the entire workflow of AI model development, including data preprocessing, model building, training, and deployment. This end-to-end capability makes TensorFlow particularly well-suited for cancer imaging research. The framework's dynamic architecture allows researchers to design and customize neural networks tailored to specific oncologic tasks, such as tumor segmentation, classification, and detection. Additionally, TensorFlow includes TensorBoard, a powerful visualization tool that enables real-time monitoring, debugging, and interpretability of models, ultimately improving model performance and explainability. TensorFlow's scalability allows efficient handling of large-scale medical imaging datasets, a critical feature given the high dimensionality and volume of oncology imaging data. These capabilities have been validated across numerous studies, demonstrating TensorFlow's effectiveness and robustness in cancer imaging applications.[119,120]

13.2. PyTorch

PyTorch, developed by the Facebook AI Research team, is a widely adopted open-source deep learning framework highly regarded in cancer imaging research. Its defining feature is a dynamic computation graph that offers greater flexibility and ease of use, especially during the prototyping and experimentation phases. Researchers appreciate PyTorch's intuitive interface, which simplifies the construction of complex neural networks for diverse oncologic tasks.

PyTorch has been extensively applied in various areas such as 3D medical image analysis, tumor segmentation, and survival prediction, demonstrating strong performance and adaptability. The growing ecosystem around PyTorch, including specialized libraries such as TorchIO for medical imaging, further enhances its utility in oncology. Additionally, PyTorch benefits from robust community support and seamless integration with other software tools, making it a preferred choice among cancer imaging researchers. Rao *et al.*[121] used an ensemble of pretrained models to handle class imbalance, achieving accuracies up to 98% in two-class and 89% in eight-class classifications. However, misclassification remains high in the ductal carcinoma (DC) class due to data imbalance. Future work may focus on expanding datasets or alternative techniques. The model was trained using two Nvidia Tesla V100 GPUs on Google Cloud.[121,122]

13.3. MONAI (Medical Open Network for AI)

MONAI (Medical Open Network for AI) is a PyTorch-based open-source framework specifically designed for medical imaging and healthcare AI research. Built on PyTorch, MONAI provides domain-optimized tools for key tasks, including tumor segmentation, classification, and image registration. It supports advanced functionalities, such as 3D image processing, multi-GPU training, and federated learning, which are essential for large-scale cancer imaging studies. One of MONAI's core strengths is its focus on reproducibility and standardization, addressing critical challenges in medical AI development. Its modular architecture and integration with commonly used imaging formats streamline preprocessing and model development workflows. Backed by a growing community and strong collaborations between academia and industry, MONAI is playing an increasingly vital role in advancing cancer imaging research.[123,124]

13.4. ITK (Insight Toolkit)

Insight Toolkit (ITK) is a robust open-source software library designed for advanced medical image analysis and processing. Widely used in cancer imaging research, ITK offers comprehensive tools for key tasks such as image registration, feature extraction, and segmentation. Its well-tested, stable architecture ensures high reliability when processing complex imaging data from modalities. ITK is often integrated with platforms such as 3D Slicer for visualization, enabling the construction of end-to-end pipelines for cancer image analysis. Its open-source availability, cross-platform support, and extensive documentation make it highly accessible and adaptable for researchers globally. These features position ITK collectively as a foundational tool in computational oncology research.[124–126]

13.5. Public datasets and repositories

Public datasets and databases play a critical role in advancing cancer imaging research by offering standardized, high-quality data for training, validating, and benchmarking AI models. One of the most widely utilized resources is The Cancer Imaging Archive (TCIA), which provides a vast repository of de-identified medical images such as CT, MRI, and PET scans, along with associated clinical metadata. TCIA supports a broad range of research applications, including tumor detection, segmentation, classification, and prediction of therapeutic outcomes.

Notable datasets include the BraTS (Brain Tumor Segmentation) dataset, which is essential for benchmarking brain tumor segmentation algorithms, and the National Cancer Institute Genomic Data Commons, which integrates imaging with genomic data to support radiogenomic studies. These public resources foster collaboration, reproducibility, and large-scale comparative studies, accelerating innovation in AI-based cancer imaging.[125]

13.6. Collaborative platforms

Open-source communities and collaborative platforms are central to accelerating innovation in cancer imaging by facilitating transparency, reproducibility, and shared development. Platforms such as GitHub and GitLab allow researchers to share codebases, pre-trained models, and processing pipelines, enabling others to reproduce results, contribute improvements, or adapt tools for new clinical applications. Collaborative competitions such as those hosted by the Grand Challenge platform drive advancements by encouraging teams to develop and benchmark AI models on standardized cancer imaging datasets under real-world conditions. Initiatives such as the NVIDIA Clara platform and the Open Health Imaging Foundation provide robust ecosystems for building, deploying, and visualizing medical imaging applications. These platforms support scalable AI model training, inference, and clinical integration. By promoting collective development and open access, such resources democratize innovation, ensuring that cutting-edge cancer imaging tools reach clinicians and researchers worldwide.[127]

14. Human–artificial intelligence collaboration in cancer care

Interoperability between clinicians and AI holds transformative potential for cancer care by fostering synergistic models that combine the analytical power of AI with the contextual judgment of human physicians. A key conceptual distinction lies in AI versus augmented intelligence. While AI may imply autonomy, augmented intelligence emphasizes AI's role as a supportive tool that enhances clinical decision-making rather than replacing the clinician. By accelerating the interpretation of complex data such as imaging, genomics, and electronic health records, AI enables clinicians to focus on personalized care, nuanced decision-making, and patient engagement.[128]

An example of this synergy is seen in Clinical Decision Support Systems (CDSS). AI-powered CDSS are increasingly integrated into oncology workflows to enhance diagnostic precision, optimize treatment planning, and reduce the risk of errors. These systems analyze large datasets, including imaging results and patient histories, to provide evidence-based recommendations that support timely, informed interventions.[128]

Looking forward, human–AI collaboration is evolving toward hybrid intelligence models, in which AI's capability to detect complex patterns and simulate outcomes complements the human clinician's empathy, ethical reasoning, and personalized insight. As AI continues to advance, tasks such as identifying subtle imaging biomarkers or predicting therapy response will be handled by machines, while physicians interpret these findings in light of each patient's unique context. This partnership promises to optimize outcomes by blending technological precision with human understanding.[129]

15. Economic and accessibility implications of artificial intelligence in cancer imaging

Artificial intelligence integration in cancer imaging holds immense promise not only for enhancing diagnostic precision but also for reducing the overall economic burden of cancer care. By automating labor-intensive tasks such as image analysis and clinical data interpretation, AI can significantly lower operational costs, reduce diagnostic errors, and expedite treatment decisions. These efficiencies contribute to long-term healthcare cost savings, especially by enabling earlier intervention and minimizing unnecessary procedures. However, the high initial cost of acquiring AI systems, including software licenses, high-performance hardware, and supporting infrastructure, remains a barrier to broader adoption, particularly in resource-limited settings.[130]

The implementation of AI in low-resource communities faces multiple challenges, including inadequate infrastructure, limited financial investment, and a shortage of skilled professionals. Advanced AI systems often require stable internet access, modern computing infrastructure, and trained personnel to deploy and maintain them, conditions that are often unmet in underserved regions. Bridging this digital divide will require strategic investments in infrastructure, capacity building, and inclusive technological design that adapts AI tools to local needs and constraints.[131]

Telemedicine combined with AI offers a powerful solution for expanding cancer care to remote and underserved populations. AI-driven remote diagnosis and real-time interpretation of imaging data can support oncologists in delivering timely and accurate assessments without requiring patients to travel long distances. This integration of AI into tele-oncology platforms enhances access to expert opinions and facilitates early diagnosis and monitoring, which are crucial in areas with limited specialist availability.[132]

A global call for health equity underpins the advancement of AI in cancer imaging. Ensuring that marginalized and low-income populations benefit from AI technologies requires overcoming structural healthcare inequalities. Solutions include providing affordable AI platforms, localized training for healthcare workers, and policy mechanisms such as technology transfer agreements, public subsidies, or tiered pricing models tailored for low- and middle-income countries.[133]

Policy recommendations should focus on expanding equitable access to AI-enabled cancer imaging. Governments, international health organizations, and private stakeholders must collaborate to fund infrastructure development, workforce training, and the integration of AI technologies into national healthcare systems. Public–private partnerships can accelerate AI adoption while ensuring that vulnerable and high-risk populations receive timely, accurate, and affordable cancer care powered by AI innovations.[134]

16. Emerging imaging modalities and their integration with artificial intelligence

Several emerging imaging modalities show substantial promise in advancing cancer diagnosis and treatment, particularly when enhanced by AI. Techniques such as photoacoustic imaging, hyperspectral imaging, and optical coherence tomography (OCT) offer high-resolution, high-sensitivity visualization of malignant tissues.

Photoacoustic imaging uniquely combines the spatial resolution of ultrasound with the molecular contrast of optical imaging. This hybrid approach enables early tumor detection by capturing both anatomical and functional information. Hyperspectral imaging captures a broad spectrum of light beyond the visible range, allowing it to differentiate tissue types based on subtle variations in optical signatures. This makes it effective for tissue characterization and tumor demarcation. OCT produces high-resolution, cross-sectional images suitable for detecting superficial cancers, such as those of the skin, oral cavity, or retina, where tissue depth is limited.[135]

Artificial intelligence plays a pivotal role in multimodal imaging fusion, where data from these novel modalities are combined with conventional imaging (e.g., CT, MRI, PET). Through advanced data integration, AI generates a more comprehensive view of tumor characteristics, including morphology, functional properties, and molecular environment. This fusion enhances diagnostic accuracy and facilitates personalized treatment planning.[136,137]

Furthermore, AI is transforming real-time intraoperative imaging. In the operating room, real-time 3D tumor visualization aids surgeons in precise tumor resection while minimizing damage to surrounding healthy tissue. AI-guided systems also improve biopsy targeting, helping clinicians navigate biopsy needles accurately to regions of interest, thereby boosting sampling precision and diagnostic yield.[138]

Despite these advantages, widespread adoption faces technical, financial, and regulatory challenges. Technical limitations include the integration of new imaging tools into existing clinical workflows and the need for specialized training. Financially, the high cost of development and deployment may restrict accessibility, particularly in low-resource settings. Additionally, these novel imaging modalities must undergo rigorous regulatory validation to establish safety, efficacy, and reproducibility before clinical adoption can expand.[139]

17. Challenges and limitations

While AI offers transformative potential in cancer imaging, its application is accompanied by significant limitations and challenges that must be addressed to ensure safe and effective integration into clinical workflows.

17.1. Data limitations

One of the primary challenges is the lack of sufficiently large and well-labeled datasets. Deep learning models require extensive annotated data for effective training, yet such datasets are often unavailable, especially for rare cancers or underrepresented populations. Additionally, heterogeneity in imaging data due to variations in imaging equipment, protocols, and patient demographics can reduce model robustness. Imaging artifacts, noise, and distortion can further degrade performance, making it difficult for AI systems to deliver reliable and consistent results across diverse clinical environments.[140]

17.2. Model-related challenges

Artificial intelligence models, particularly deep learning architectures, are prone to overfitting: they perform well on training data but fail to generalize to unseen, real-world cases. This lack of generalizability is especially problematic in the variable landscape of clinical medicine. Furthermore, most current models lack explainability, providing little insight into how diagnostic decisions are made. This "black-box" nature can reduce clinician trust, hinder adoption, and complicate shared decision-making. Transferability is another concern: models trained on datasets from specific institutions or imaging systems often perform poorly when applied to data from other hospitals, countries, or devices, limiting scalability and global utility.[141]

17.3. Regulatory and ethical barriers

Implementing AI in cancer imaging also raises complex regulatory and ethical considerations. Ensuring data privacy and security is paramount, as medical data are highly sensitive and susceptible to misuse or cyber threats. Bias in AI algorithms remains a pressing concern—models trained on non-diverse datasets may perpetuate healthcare disparities by underperforming in certain populations. Moreover, AI systems must undergo rigorous clinical validation to prove safety and efficacy, a process that is often time-intensive, costly, and complex, yet essential for regulatory approval and widespread clinical acceptance.[142]

18. Future directions and innovations in artificial intelligence-based cancer imaging

In the coming years, several innovative trends are poised to significantly advance AI applications in cancer imaging, addressing current limitations and enhancing clinical utility.

18.1. Self-supervised and federated learning

Self-supervised learning is gaining momentum as a powerful strategy for overcoming the scarcity of labeled medical imaging data. This approach allows AI models to learn meaningful patterns from large volumes of unlabeled data, significantly reducing dependence on expert annotation. It enhances model generalizability and adaptability, even in resource-limited settings.[143]

Federated learning is another transformative trend. It enables collaborative AI model training across multiple healthcare institutions without requiring data to leave its original location, thus preserving patient privacy and complying with data protection regulations. This decentralized model leverages diverse datasets, improving model robustness while minimizing security risks.[144]

18.2. Explainable artificial intelligence

As AI systems become integral to clinical workflows, the need for explainability has grown. XAI approaches aim to make model predictions transparent and understandable to clinicians by highlighting the rationale behind decisions. Enhanced interpretability increases physician trust, facilitates regulatory approval, and supports shared decision-making in high-stakes cancer diagnosis.[143]

18.3. Quantum computing in medical imaging

Quantum computing offers unprecedented computational power to process and analyze massive volumes of imaging and multi-omics data. Its potential to drastically accelerate image reconstruction and tumor pattern recognition could revolutionize early cancer detection, risk stratification, and personalized treatment planning.[144]

18.4. Personalized and precision imaging

The future of cancer imaging is increasingly patient-specific. AI-driven platforms are moving toward precision imaging, where analysis is tailored to an individual's genetic, clinical, environmental, and lifestyle data. This integrative approach facilitates more accurate diagnosis, prognosis, and treatment decisions, laying the foundation for truly personalized cancer care.[145,146]

19. Case studies and practical implementations

Artificial intelligence has demonstrated its practical utility and clinical feasibility in real-world cancer imaging settings. AI-powered diagnostic systems are now actively used in cancer institutes to assist clinicians, enhance diagnostic accuracy, and streamline decision-making processes. For example, AI-assisted interpretation of mammograms has shown performance equal to or exceeding that of experienced radiologists in early breast cancer detection. These tools not only improve the quality of diagnoses but also alleviate radiologists' workload, allowing specialists to concentrate on more complex or ambiguous cases.[146]

In clinical practice, AI algorithms have proven effective in analyzing subtle imaging patterns associated with tumor recurrence, metastasis, and treatment response. By generating early warnings from nuanced image data, these systems facilitate timely interventions, ultimately improving patient survival and health outcomes. Moreover, AI-enhanced radiotherapy planning contributes to more precise radiation delivery, reducing collateral damage to healthy tissues and minimizing adverse side effects.[147]

Ongoing clinical trials and research collaborations further validate AI's transformative role in oncology. Collaborative initiatives between hospitals, academic institutions, and AI companies have led to the development and deployment of customized AI tools in clinical workflows. These partnerships demonstrate how AI models can be adapted to specific real-world applications across various cancer types, reinforcing their reliability, adaptability, and impact in precision oncology.[148]

20. Conclusion

This study highlights the transformative role of AI and image processing in cancer detection, diagnosis, prediction, and prognosis. Over the past decade, advances in medical imaging and machine learning have significantly enhanced early cancer detection, diagnostic precision, and treatment personalization. AI-powered pattern recognition systems improve accuracy, reduce diagnostic delays, and support more targeted interventions, ultimately improving patient outcomes.

The strength of AI lies in its ability to analyze vast imaging datasets quickly and precisely, identifying subtle patterns beyond human perception. These technologies can predict cancer recurrence, metastasis, and treatment response, enabling clinicians to tailor therapies with greater confidence. However, challenges persist. The reliability of AI models is contingent on access to large, diverse, and high-quality datasets. Incomplete or biased data can yield misleading results. Moreover, the interpretability of deep learning models, often considered "black boxes," remains a critical barrier to clinical trust and integration.

Despite these limitations, emerging innovations such as self-supervised learning and quantum computing are pushing AI beyond current constraints. These advancements promise faster data processing and reduced dependency on labeled datasets, paving the way for real-time clinical decision support.

To fully realize AI's potential in oncology, interdisciplinary collaboration is essential. Oncologists, data scientists, ethicists, and policymakers must work together to address ethical, technical, and logistical challenges. Ensuring equitable access and responsible deployment will be key to maximizing the benefits of AI for all cancer patients, regardless of socioeconomic status or geographic location. In summary, while hurdles remain, AI holds immense promise for revolutionizing cancer care, enabling earlier detection, more effective and personalized therapies, and a better quality of life for millions worldwide.

Acknowledgments

We would like to thank the participants for their patience and kindness.

Funding

None.

Conflict of interest

The authors declare no conflicts of interest.

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Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data

Not applicable.

Further disclosure

The article has been published on Preprints.org: Sah AK, Agarwal S, Abbas AM, *et al.* Advances in Image Processing and Pattern Recognition in Cancer Detection, Prediction, Diagnosis, and Prognosis. March 2025. doi: 10.20944/preprints202503.0055.v1

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