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Review

The evolving landscape: Role of artificial intelligence in cancer detection

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Abstract: Artificial intelligence (AI) has played a major role in recent developments in healthcare, particularly in cancer diagnosis. This review investigated the dynamic role of AI in the detection of cancer and provides insights into the fundamental contributions of AI in the revolutionization of cancer detection methodologies, focusing on the role of AI in radiology and medical imaging and highlighting AI's advancements in enhancing accuracy and efficiency in identifying cancerous lesions. Furthermore, it explained the indispensable role of pathology and histopathology in cancer diagnosis, emphasizing AI's potential to augment traditional methods and improve diagnostic precision. Genomics and personalized medicine were explored as integral components of cancer detection, illustrating how AI facilitates tailored treatment strategies by analyzing vast genomic datasets. Additionally, the discussion encompassed clinical decision support systems, explaining their utility in aiding healthcare professionals with evidence-based insights for more informed decision-making in cancer detection and management. Finally, the review addressed the challenges and future directions in the integration of AI into cancer detection practices, highlighting the need for continued research and development to overcome existing limitations and realize the full potential of AI-driven solutions in combating cancer.

Keywords: artificial intelligence; deep learning; machine learning; cancer detection

Abbreviations: AI: Artificial intelligence; WHO: World Health Organization; DL: Deep learning; ML: Machine learning; MRI: Magnetic Resonance Imaging; CT: Computed Tomography; KNN: K-nearest neighbors; SVM: Support Vector Machine; CNN: Convolutional neural network; NN: Neural network; GNN: Generative adversarial network; PET: Position Emission Tomography; FDA: Food and Drug Administration; CAD: Computer-assisted diagnosis; FFDM: Full Field Digital Mammography; AiCE: Advanced intelligent Clear IQ Engine; FBP: Filtered back projection; SPECT: Single-photon emission computed tomography; DWI: Diffusion-weighted imaging

1. Introduction

As per the report of the World Health Organization (WHO), approximately 10 million people globally were affected by cancer in 2020 [1,2]. Breast cancer accounted for 2.26 million cases, lung cancer for 2.21 million, rectum and colon cancer for 1.93 million, skin cancer for 1.20 million, and stomach cancer for 1.09 million [2]. In India, nearly 2.7 million people are affected by cancer and every year, 13.9 one hundred thousand new cancer patients are identified [2]. Overall, according to cancer statistics in India (2020), 8.5 one hundred thousand deaths are caused by the cancer. Figure 1 shows the distribution of cancer-related deaths in both male and female populations for the year 2021. Among various cancer types, lung and bronchus cancer reflect a significant proportion of cases. The data underscores the critical impact of cancer on public health, highlighting the urgency of targeted interventions and research efforts.

The incidence and complexity of cancer pose a serious threat to world health, necessitating novel strategies for earlier identification and better management. A new age in healthcare has begun with the introduction of AI, which has shown promising results in cancer detection, diagnosis, and therapy. This review paper explores various domains in which AI may be helpful in the identification of cancer, emphasizing its benefits for early diagnosis, precise treatment, and patient-centered care. A key element determining treatment success and patients' survival rates is early cancer identification. Traditional diagnostic techniques frequently rely on the arbitrary interpretation of pathology and radiology scans by individuals. However, AI systems have shown impressive results in improving the diagnosis procedure. Deep learning (DL) methods allow AI models to precisely recognize tiny irregularities and medical imaging patterns that aid in early detection and lower false negatives [3].

These advancements have the potential to impact cancer management and patient prognosis significantly. Additionally, AI-driven risk prediction models have emerged as valuable tools for identifying individuals at high risk of developing specific cancers. Through the analysis of diverse datasets that encompass genetic, lifestyle, and clinical information, AI algorithms can stratify individuals based on their susceptibility to certain malignancies. This stratification enables the tailoring of personalized screening protocols and preventive interventions, contributing to improved early detection rates [4,5]. Precision medicine, another paradigm-shifting concept, relies on the understanding of individual patient's unique genetic and molecular profiles to guide treatment decisions. AI's capability to process large-scale genomic datasets has fueled the discovery of novel biomarkers and genetic mutations associated with cancer susceptibility and progression [6,7]. These insights empower oncologists to design personalized treatment regimens, thereby increasing the likelihood of therapeutic success and minimizing adverse effects. In addition to diagnostics and precision medicine, AI technologies have revolutionized treatment planning and monitoring. Real-time analysis of patient data, coupled with machine learning (ML) algorithms, empowers healthcare professionals to dynamically adjust treatment strategies based on evolving patient responses [8,9]. Such capabilities promote a patient-centric approach to cancer care, optimizing treatment efficacy and enhancing the quality of life for individuals undergoing therapy. However, the integration of AI into cancer detection is not devoid of challenges. Data privacy concerns, the need for robust validation, and the potential biases in algorithmic decision-making warrant careful consideration [10,11]. Collaboration between clinicians, data scientists, and regulatory bodies is essential to ensure a responsible and ethical development of AI technologies in oncology [12,13].

This review article comprehensively explores the multifaceted applications of AI in cancer detection, encompassing radiology, pathology, genomics, and clinical decision support systems. By examining the current state of the field, addressing challenges, and envisioning future directions, the study aims to elucidate the transformative impact of AI on reshaping the landscape of cancer detection and care, ultimately contributing to improved patient outcomes.

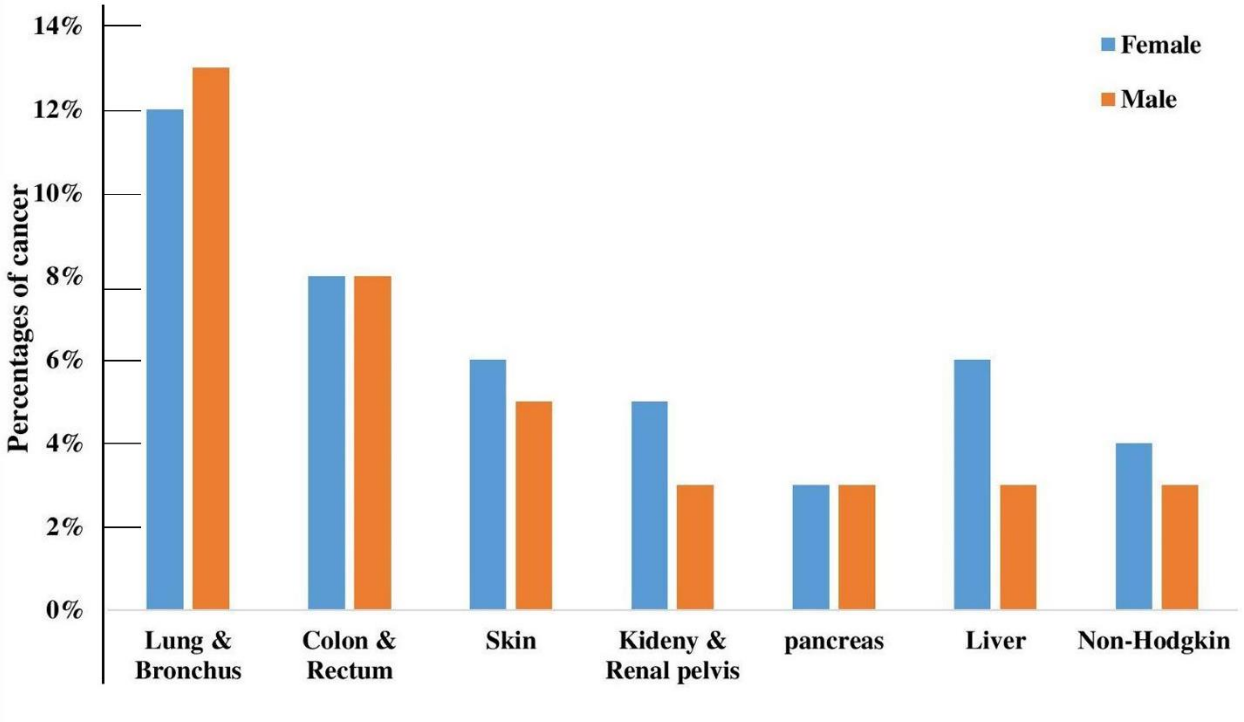

Figure 1. Comparative analysis of cancer mortality in male and female populations for 2021 [2].

2. Overview of the role of artificial intelligence in cancer detection

The role of AI in cancer detection is becoming increasingly significant due to its potential to enhance accuracy and efficiency in the assessment of risk and early diagnosis [2,5–8]. AI tools, particularly ML and DL, are revolutionizing the field of oncology by assisting medical professionals in identifying cancerous tissues and anomalies with improved precision [3]. The AI algorithms, particularly spatial algorithms, leverage data from various cancer diagnostic techniques such as magnetic resonance imaging (MRI), computed tomography (CT) scans, and blood tests, enabling quicker and more accurate cancer diagnoses compared to traditional methods. Beyond diagnosis, AI is employed for treatment planning and patient monitoring, thereby contributing to improved patient outcomes. In the realm of cancer detection, AI's subfield of ML focuses on using data and algorithms to learn and predict events with minimal human involvement. This capability finds applications in various domains including medical diagnostics, speech recognition, email screening, and more. ML algorithms such as random forest, K-nearest neighbors (KNN), and support vector machine (SVM) can expedite and enhance cancer identification. For example, the random forest method has demonstrated its ability to identify early-stage breast cancer by utilizing imaging data effectively [6]. As AI continues to evolve, it holds the promise of further transforming cancer detection and diagnosis, optimizing the utilization of medical data to provide timely and accurate insights that benefit both patients and medical professionals [14,15]. Figure 2 illustrates the sequential steps required for the preparation of a predictive ML model. These steps are crucial to ensure optimal model performance and the accurate generalization of predictions to new data.

2.1. Defining the problem

The initial step involves precisely articulating the problem that ML is going to address. Understanding the core business or research objective and the specific predictions or classifications is an essential step.

2.2. Data collection and preprocessing

Data serves as the foundation of any ML model. Relevant data should be collected to address the identified problem. The data must be clean, organized, and reflective of real-world scenarios. Data preprocessing tasks, including cleaning, normalization, and feature extraction may be necessary.

2.3. Splitting the data

Dividing the dataset into distinct subsets is crucial. The data is typically divided into training, validation, and test sets. The validation set assists in fine-tuning hyperparameters, the test set evaluates the final model's performance on previously unseen data, and the training set is used to train the model.

2.4. Choosing an algorithm

Selecting an appropriate ML algorithm depends on the problem type (classification, regression, clustering, etc.) and the characteristics of the dataset. Common algorithms such as decision trees, random forests, support vector machines, and neural networks can be considered.

2.5. Building the model

Once the algorithm is chosen, it is time to implement it using a suitable ML library like scikit-learn, TensorFlow, or PyTorch. This involves configuring hyperparameters that control the learning process and training the model on the training data.

2.6. Validating and tuning

Validation and tuning are essential steps to refine the model's performance. Minor adjustments to hyperparameters can be made using the validation set. This process, known as hyperparameter tuning, helps determine the optimal configuration of settings to enhance the model's efficacy.

The steps outlined above provide a comprehensive framework for preparing a cancer detection model using ML. By following these steps, one can systematically approach the development of a predictive model that aims to detect cancer with accuracy and reliability. From defining the problem and data collection to selecting an appropriate algorithm and fine-tuning the model, each step contributes to creating a robust and effective cancer detection solution.

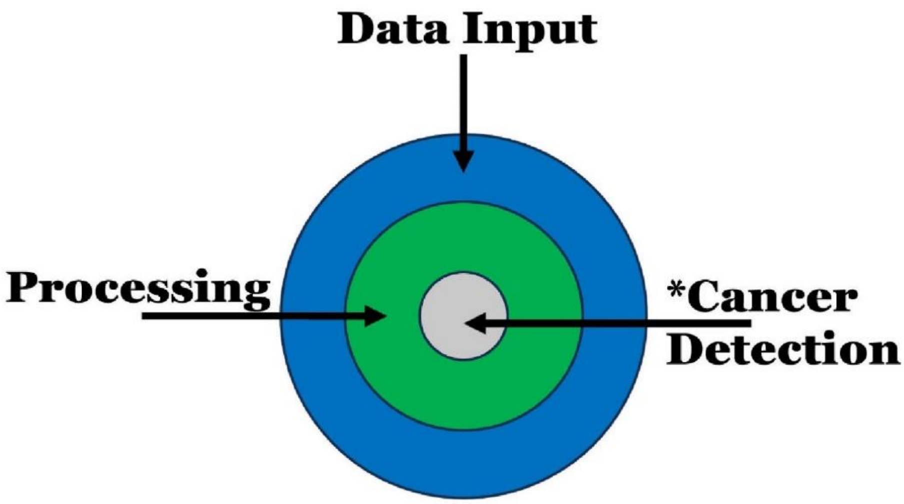

Figure 2. Schematic representation of machine learning model structure.

One common approach is using an ML algorithm to identify patterns indicative of cancer. For example, convolutional neural networks (CNNs) can analyze medical images like X-rays and MRI, while decision tree or SVM can process the genetic data. These algorithms can help doctors make more accurate diagnoses [14,16]. Random forest is an effective algorithm for cancer detection because it can capture complex relationships in the data, handle noise, and reduce the risk of overfitting [15,16]. Parameter tuning and feature selection are crucial in optimizing the algorithm's performance for specific datasets and cancer types.

DL, as opposed to ML, processes enormous volumes of unstructured data using multi-layered structures known as neural networks (NN). Deep learning is a subfield of ML that involves employing complex algorithms and deep NN to train a model. Applications for DL are utilized in image colorization, self-driving automobiles, and robotics. Deep learning assists in making therapeutic decisions and greatly improves the precision with which malignant tumors in the human body are detected. GAN (generative adversarial network) is a deep learning model used to improve breast cancer identifications by generating synthetic mammographic images for screening purposes. This method helps to address the limitations of data scarcity and improves the robustness of detection algorithms [14–16]. For example, Rezaei et al. developed a hierarchical GAN method with an ensemble CNN for accurate nodule detection in lung cancer diagnosis with a 30% improvement in detection rate [17]. Similarly, Alruily et al. introduced a hybrid approach as shown in Figure 3 for augmentation and segmentation of breast ultrasound images using GAN to identify blocks and modified Net 3+, showing efficient results in both augmentation and segmentation steps [14–16,18].

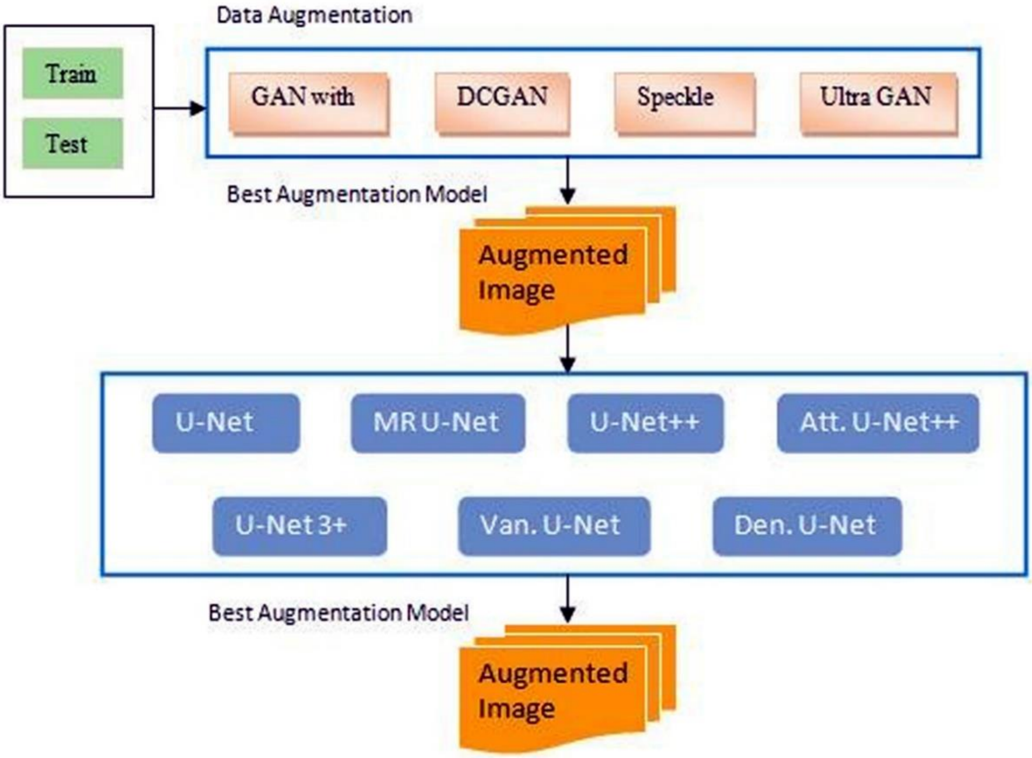

Figure 3. Schematics of the methodology block diagram.

The conventional use of technology in diagnosis includes X-rays, MRIs, CT scans, Position Emission Tomography (PET) scans, ultrasounds, and biopsies that are then subjected to microscopic examination. Techniques such as cryo-electron microscopy, Infinium assay, robotic surgery, CRISPR (clustered regularly interspaced short palindromic repeats), cryoablation, and radiofrequency ablation contemporary tools are used for treatment [14–16,19]. Table 1 shows the list of medical devices equipped with AI technology that have been approved by the US Food and Drug Administration (FDA) for use in cancer radiology-related applications.

Table 1. Year-wise summary of medical devices equipped with AI technology that have been approved by the US FDA for use in cancer radiology-related applications [20].

Serial number	Year of approval	Name of the device	Description of the device and its role
1.		ClearRead CT (Riverain Technologies LLC.)	Providing support for reviewing chest multi-slice CT scans and identifying potential nodules that require a radiologist's attention.
2.	2015	Transpara (ScreenPoint Medical BV)	Aiding physicians in the interpretation of screening mammograms, aiding in the identification of suspicious areas indicative of breast cancer.

Continued on next page

Serial number	Year of approval	Name of the device	Description of the device and its role
3.	2016	SmartTarget (SmartTarget Ltd.)	Participating in image-guided intervention and diagnostic procedures related to the prostate gland.
4.		LungQ (Thirona Corp.)	Aiding in diagnosing and documenting abnormalities in pulmonary tissue images, specifically extracted from CT thoracic datasets.
5.	2017	AmCAD-US (AmCad BioMed Corporation)	A software designed to visualize and quantify ultrasound image data along with corresponding backscattered signals.
6.		QuantX (Quantitative Insights)	An AI-enhanced diagnostic system designed to assist in achieving accurate diagnoses of breast cancer.
7.		Veye Chest (Aidence BV)	Assistance in the detection of pulmonary nodules from CT scans.
8.	2018	Arterys Oncology DL (Arterys)	An AI-powered, cloud-based medical imaging software designed to automatically measure and track lesions and nodules in both MRI and CT scans.
9.		QVCAD (QView Medical Inc.)	An assistance tool aimed at detecting mammography-occult lesions in areas that were not initially identified as having suspicious findings.
10.		HealthMammo (Zebra Medical Vision Inc.)	Processing and analyzing mammograms to identify suspected lesions indicative of breast cancer.
11.		Arterys Oncology DL (Arterys Inc.)	Assisting in the oncological workflow by aiding users in confirming the presence or absence of lesions. This application supports anatomical datasets such as CT or MRI scans.
12.		AmCAD-UT (AmCad BioMed Corporation)	Providing support in the analysis of thyroid ultrasound images.
13.		Mia -Mammography Intelligent Assessment (KheironMedical Technologies Ltd.)	Offering assistance in the detection of breast cancer through the analysis of mammograms.
14.		Arterys MICA (Arterys)	A platform powered by AI for the analysis of medical images, including MRI and CT scans.
15.		SubtlePET (Subtle Medical)	An AI-driven technology that enables medical centers to provide quicker and safer patient scanning experiences, simultaneously improving exam throughput and provider profitability.

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Serial number	Year of approval	Name of the device	Description of the device and its role
16.		carriage (CureMetrix)	A software utilizing AI for the triage of mammography cases.
17.		Deep Learning Image Reconstruction (GE Medical Systems)	
18.		Auto Lung Nodule Detection (Samsung Electronics Co. Ltd. (parent company: Samsung Group)	Breast cancer detection for diagnostic support from mammograms.
19.		JPC-01K (JLK Inspection Inc.)	Offering diagnostic support through the detection of prostate cancer using MRI.
20.		syngo.Breast Care (Siemens Healthcare GmbH (parent company: Siemens AG))	Providing interpretation and reporting services to offer diagnostic support using mammograms.
21.	2019	Aquilion ONE (TSX-305A/6) V8.9 with AiCE (Canon MedicalSystems Corporation)	A device capable of capturing and displaying cross-sectional volumes of the entire body, including the head, with the unique ability to image whole organs within a single rotation.
22.		ProFound AI for Digital Breast Tomosynthesis (iCAD Inc.)	A software device for computer-assisted detection and diagnosis (CAD) designed to aid in the interpretation of digital breast tomosynthesis (DBT) exams.
23.		RayCare 2.3 (RaySearch Laboratories)	An oncology information system is utilized to facilitate workflows, scheduling, and the management of clinical information for oncology care and post-treatment monitoring.
24.		Breast-SlimView (Hera-MI SAS)	Providing diagnostic support by detecting breast cancer through the analysis of mammograms.
25.		Vara (Merantix Healthcare GmbH)	Assistance in breast cancer screening and triage through the analysis of mammograms.
26.		ProFound AI Software V2.1 (iCAD)	A Computer aided design (CAD) software device was developed to be used simultaneously by interpreting physicians during the assessment of DBT images.

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Serial number	Year of approval	Name of the device	Description of the device and its role
27.		Transpara (ScreenPoint Medical)	A device designed to assist physicians concurrently while interpreting screening mammograms from compatible Full Field Digital Mammography (FFDM) systems. Its purpose is to help identify regions that appear suspicious for breast cancer and evaluate the likelihood of malignancy.
	2019		
28.		QyScore software (Qynapse SAS)	Automating the process of labeling, visualizing, and quantifying the volumes of segmentable brain structures and lesions from MRI images.
29.		JBD-01K (JLK Inspection Inc.)	Providing diagnostic support through the detection of breast cancer using mammograms.
30.		InferRead CT Lung (Beijing Infervision Technology Co. Ltd.)	A tool designed for lung cancer screening and management through the analysis of CT scans.
31.		b-box (X-rays GmbH)	Evaluating the quality of mammography images and determining breast density using mammograms.
32.		densitasAI (Densitas Inc.)	Offering support for the assessment of breast density using mammograms.
33.	2020	Broncholab (Fluidda Inc)	Aiding in diagnosing and documenting abnormalities in pulmonary tissue images obtained from CT thoracic datasets.
34.		Syngo.CT Lung CAD (Siemens Medical Solutions Inc. (parent company: Siemens AG))	Aiding in the detection of solid pulmonary nodules while reviewing multi-detector computed tomography (CT) exams of the chest.
35.		Genius AI Detection (Hologic, Inc.)	A software device designed to detect potential abnormalities in breast tomosynthesis images.
36.		MammoScreen (Therapixel SA)	Assisting in the identification of findings on screening FFDM acquired with compatible mammography systems and evaluating the level of suspicion associated with them.
37.		Visage Breast Density (Visage Imaging)	The software application is designed to be utilized alongside compatible full-field digital mammography systems, supporting radiologists in evaluating breast tissue composition.
38.		Imagio Breast Imaging System (Seno Medical Instruments, Inc.)	Enables an enhanced classification of breast masses in comparison to using ultrasound alone, incorporating AI-based software

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Serial number	Year of approval	Name of the device	Description of the device and its role
39.		Vivo Software Application (DiA Imaging Analysis Ltd.)	It provides an objective automated AI-based ejection fraction analysis.
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40.	2021	Vantage Galan 3T, MRT-3020, V6.0 with AiCE Reconstruction Processing Unit for MR Canon Medical Systems Corporation	Advanced intelligent Clear IQ Engine (AiCE) MRI deep learning reconstruction has been used for the construction of MR images.
41.		GI Genius Cosmo Artificial Intelligence - AI Ltd	It helps physicians detect colorectal polyps of various sizes, shapes, and morphologies.
42.		Chest-CAD Imagen Technologies, Inc	The average clinician missed the spot or showed a misinterpretation rate of 47%. This helps to identify the spot by using AI.
43.		Precise Image (Philips Medical Systems Nederland, B.V.)	AI-powered reconstruction algorithm designed for the low radiation dose, which helps to improve the image appearance that closely resembles filtered back projection (FBP) at a higher dose.
44.		Contour ProtegeAI MIM Software Inc.	It uses the machine learning algorithms for processing of CT images.
45.	2022	Deep Learning Image Reconstruction GE Medical Systems	It uses the deep learning imaging reconstruction algorithm trained to eliminate image noise by leveraging MRI raw data.
46.		Ingenia, Ingenia CX, Ingenia Elition, Ingenia Ambition, MR 5300 and MR 7700 MR Systems Philips Medical Systems Nederland B.V.	It enables physicians to obtain cross-sectional and spectroscopic images.
47.		Brainomix 360 Triage ICH Brainomix Limited	It is a notification tool that provides real-time alerts to clinicians.

3. Role of radiology and medical imaging in cancer detection

Mainly, there are six imaging modalities available to treat human cancer: X-ray, PET, optical imaging, single-photon emission computed tomography (SPECT), Ultrasound (US), and MRI. Table 2 discusses the methods that play an important role in the detection of the infected part or organ where cancer cells are located. The use of AI has emerged as a transformative force in radiology and medical imaging, reshaping how medical professionals interpret and analyze complex imaging data. AI-driven algorithms offer the potential to enhance accuracy, efficiency, and diagnostic capabilities across a range of imaging modalities. In diagnostic radiology, AI aids in detecting and characterizing anomalies, from subtle lesions to intricate patterns, by leveraging DL techniques that learn from vast datasets. For instance, AI-powered systems have demonstrated remarkable performance in detecting abnormalities in chest X-rays, aiding in the early diagnosis of conditions like pneumonia and lung cancer. Recently, Google Health has developed a deep learning model that can distinguish between normal and abnormal chest radiographs across multiple datasets, including tuberculosis and COVID-19 cases [21]. Additionally, AI assists in the triage and prioritization of cases, optimizing workflow and improving patient care [22–25]. In medical imaging, AI holds potential in advanced modalities such as MRI and CT [26]. Zou et al. developed a new framework for dynamic reconstruction of MRI images. This framework splits the under-sample k-space measurements into two sub-datasets and uses them as inputs for two neural networks that pose the same structure but different weights [27]. Similarly, Artesani et al. explored the use of AI to revolutionize PET imaging. The study focuses on enhancing image quality, denoising, attenuation map generation, and quantification using deep learning techniques. Applications include cancer diagnosis and therapy, neurology, and cardiology [28]. AI algorithms are employed to enhance image quality, reduce artifacts, and expedite image reconstruction. Moreover, AI-driven image segmentation aids in the precise delineation of anatomical structures and assists in treatment planning, particularly in radiation therapy and surgical interventions. While the integration of AI in radiology offers transformative benefits, it also raises considerations related to algorithm robustness, clinical validation, and ethical implications, necessitating close collaboration between radiologists, data scientists, and regulatory bodies to harness AI's potential effectively [29,30]. AI integration into radiology and medical imaging has the potential to revolutionize clinical practice, enhancing diagnostic accuracy, optimizing workflows, and ultimately improving patient outcomes. However, continued research, validation, and responsible implementation remain essential for unlocking AI's full potential in this field.

Table 2. Methods involved in the detection of cancer.

Imaging method	Application	Advantages	Disadvantages	References
X-ray	X-rays are commonly used to detect tumors, bone abnormalities, and other abnormalities in the body. They are often used in combination with other imaging techniques to provide a more comprehensive view.	High sensitivity and specificity for detecting metabolic changes in cancer cells. Provides quantitative data on tracer uptake, aiding in treatment response assessment. Can be combined with computed tomography (PET/CT) for precise anatomical localization. Widely used for staging, restaging, and monitoring therapy response.	Limited spatial resolution compared to other imaging modalities. Requires the use of a cyclotron for on-site production of short-lived radionuclides. Radiation exposure to patients and healthcare professionals due to the use of radionuclides.	Malik et al., 2023 and Miwa et al., 2017 [31,32]

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Imaging method	Application	Advantages	Disadvantages	References
MRI	MRI uses a strong magnetic field and radio waves to produce images of the body’s internal structure. MRI is valuable for imaging soft tissues and can provide information about the extent and location of tumors.	Excellent soft tissue contrast, allowing for detailed anatomical visualization. No ionizing radiation, making it safer for repeated imaging. Can provide functional information through techniques like diffusion-weighted imaging (DWI) and dynamic contrast-enhanced MRI (DCE-MRI). Suitable for imaging various parts of the body.	Relatively long imaging times can be challenging for some patients. Expensive equipment and higher operational costs. Limited availability in some regions.	Aisen et al., 1986 and Siegel, 2001 [33,34]
Ultrasound	Ultrasound uses high-frequency sound waves to create images of internal structures. It is commonly used to assess the size and characteristics of tumors, guide biopsies, and monitor treatment responses.	Real-time imaging with no ionizing radiation exposure. Non-invasive and widely available. Relatively low cost compared to other imaging modalities. Suitable for guiding biopsies and minimally invasive procedures.	Limited penetration through bone and air-filled structures. Limited ability to visualize soft tissues in deep body regions. Operator-dependent and potential for variability in image quality.	Fischerova et al., 2011 [35]
PET	PET scans involve injecting a small amount of radioactive material into the body, which accumulates in areas with high metabolic activity (such as cancer cells). The PET scanner detects the radiation emitted by the material and produces images that highlight these active areas. A PET scan is often combined with a CT scan (PET/CT) for more accurate localization.	High sensitivity and specificity for detecting metabolic changes in cancer cells. Provides quantitative data on tracer uptake, aiding in treatment response assessment. Can be combined with computed tomography (PET/CT) for precise anatomical localization. Widely used for staging, restaging, and monitoring therapy response.	Limited spatial resolution compared to other imaging modalities. Requires the use of a cyclotron for on-site production of short-lived radionuclides. Radiation exposure to patients and healthcare professionals due to the use of radionuclides.	Czernin et al., 2002 [36]

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Imaging method	Application	Advantages	Disadvantages	References
SPECT	SPECT is a nuclear medicine imaging technique that provides three-dimensional images of the distribution of radioactive substances in the patient's bloodstream. The radiotracer emits gamma rays, which are detected by a gamma camera as the patient is positioned within the SPECT scanner. SPECT is particularly useful for imaging internal organs and tissues, and it has applications in cancer detection and staging.	Useful for functional imaging of specific organs and tissues. Provides valuable information on perfusion, blood flow, and receptor expression. Can be used with a variety of radiopharmaceuticals for different applications.	Lower spatial resolution compared to PET or CT. Longer imaging acquisition times compared to PET. Limited sensitivity in detecting low-level tracer uptake.	Keown et al., 2020 [37]
Sentinel lymph node mapping	In cancer staging, sentinel lymph nodes (the first lymph nodes to receive drainage from a tumor) are crucial indicators of cancer spread. Radioactive tracers are injected near the tumor, and nuclear imaging helps identify and biopsy these nodes, aiding in accurate staging.	Minimally invasive technique for identifying sentinel lymph nodes. Helps avoid unnecessary lymph node dissection in certain cancers. Accurate staging of cancer spread through lymphatic pathways.	May result in false negatives due to the possibility of missing metastatic nodes. In certain cases, sentinel nodes may not accurately represent the overall lymph node status.	Manca et al., 2016 and Petousis et al., 2022 [38,39]
Mammo graphy	Mammography is a widely used technique for breast cancer detection and screening. It involves X-ray imaging of the breast tissue to identify abnormalities such as masses or microcalcifications that may indicate the presence of cancer.	Effective for detecting breast cancer at early stages, especially in older women. Wide availability and established screening programs. Relatively low radiation exposure. Can detect small calcifications associated with early breast cancers.	Limited sensitivity in dense breast tissue, especially in younger women. Potential discomfort during compression for some patients. May result in false positives that require additional testing and anxiety.	Pisano et al., 2006 [40,41]

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Imaging method	Application	Advantages	Disadvantages	References
Thermography	Thermography detects changes in skin temperature, and it has been explored as an adjunctive tool for breast cancer screening. Increased blood flow and metabolic activity in tumors can cause temperature differences, which thermography aims to visualize.	Non-invasive and no ionizing radiation exposure. Can detect temperature changes associated with increased blood flow in some tumors. Can be used as an adjunctive tool for breast cancer detection.	Limited sensitivity and specificity compared to other imaging modalities. Variability in results due to external factors like room temperature. Not widely accepted as a primary screening tool due to its limitations.	Arora et al., 2008 [42]
Microscopy	Microscopy, including light microscopy and electron microscopy, is used for detailed examination of tissue samples obtained through biopsies. It provides insights into cellular and tissue morphology, helping pathologists identify cancerous changes and characterize tumors.	Provides high-resolution imaging of tissue samples at the cellular and subcellular level. Can reveal detailed morphological and histological information. Important for diagnostic confirmation and understanding tumor characteristics.	Invasive technique requiring tissue samples (biopsies). Limited to ex vivo analysis and may not capture dynamic processes. Labor-intensive and time-consuming for comprehensive analysis.	Kumar et al., 2014 and Mills et al., 2006 [43,44]
Radionuclide bone scans	Bone scans using radiolabeled bisphosphonates or phosphonates help detect metastatic bone disease. They can identify areas of increased bone turnover, indicating the presence of cancer metastases.	Sensitive for detecting bone metastases and assessing overall skeletal health. Allows visualization of multiple skeletal sites in a single scan. Can provide early detection of bone metastases before they become symptomatic.	Limited anatomical detail compared to CT or MRI. Cannot distinguish between active cancer lesions and non-malignant conditions like arthritis. High sensitivity can lead to false-positive findings.	Coleman et al., 2001 [45]
Thyroid cancer imaging	Radioactive iodine (iodine-131) is used to diagnose and treat thyroid cancer. Thyroid cancer cells take up iodine, allowing for imaging and targeted treatment.	Effective for imaging thyroid tissue and thyroid cancer metastases. Allows for targeted therapy using radioactive iodine-131.	Limited application to thyroid and thyroid-related conditions. The long half-life of iodine-131 requires special precautions for patient and public safety. Not suitable for cancers that do not take up iodine, such as some types of thyroid cancer.	Jin et al., 2018 and Brose et al., 2012 [46,47]

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Imaging method	Application	Advantages	Disadvantages	References
Peptide receptor radionuclide therapy (PRRT)	PRRT involves targeting cancer cells that overexpress specific receptors with radiolabeled peptides. It is used for neuroendocrine tumors and some types of prostate cancer.	Targets specific receptors on cancer cells, reducing damage to normal tissues. Can provide palliative treatment for certain types of neuroendocrine tumors. Offers a personalized approach to cancer treatment.	Limited to tumors that express the specific receptors targeted by the radiolabeled peptides. Long imaging and treatment times due to the radioactive decay of the radionuclides. Potential side effects related to radiation exposure and peptide therapy.	Strosberg et al., 2017 [48]

4. Pathology and histopathology for cancer detection

In histopathology, the examination of tissue specimens for cancer diagnosis and grading has traditionally been a labor-intensive process (Figure 4). AI-driven algorithms have significantly expedited this process by automating tasks such as tumor segmentation, cell classification, and identification of histological features [5]. Table 3 represents the list of pathology tools used for the detection of cancer. DL models trained on extensive pathological image datasets have demonstrated comparable performance to expert pathologists in diagnosing various cancers, including breast, lung, and prostate cancers [5,49]. The integration of AI into pathology not only accelerates diagnosis but also enhances consistency and reduces inter-observer variability, thereby contributing to improved patient care [49].

Recent advancements in AI have led to the development of computer-aided CAD systems that assist pathologists in identifying subtle morphological patterns indicative of malignancy [5,49]. These AI systems can highlight regions of interest, such as potential tumor areas, for pathologists to review, enhancing their efficiency and accuracy. Moreover, AI-powered algorithms aid in predicting disease prognosis and guiding treatment decisions based on histopathological features [49]. By analyzing a multitude of data points within pathology slides, AI provides valuable insights into disease progression, enabling more informed and personalized therapeutic strategies.

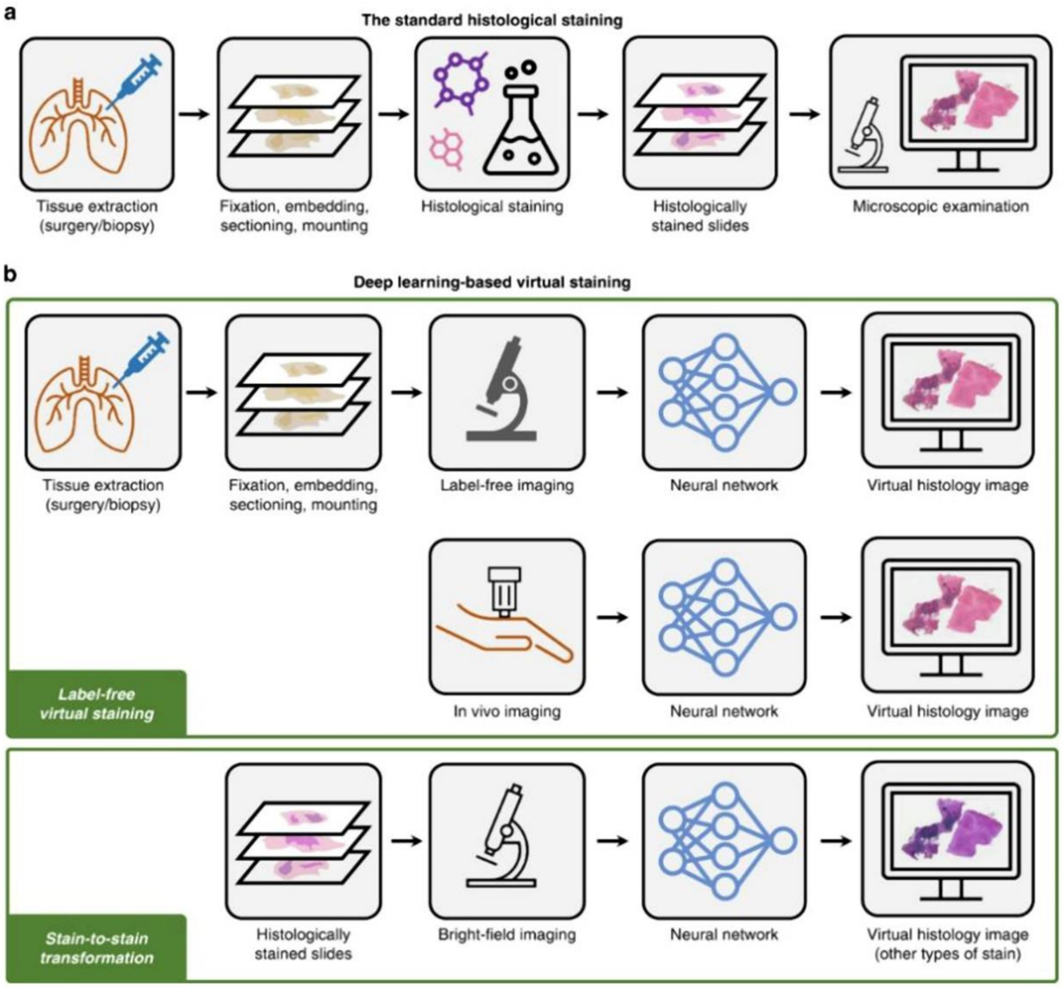

Figure 4. Standard histological staining relies on laborious chemical-based tissue processing and labeling steps. Pre-trained deep neural networks enable the virtual histological staining of label-free samples as well as the transformation from one stain type to another, without requiring any additional chemical staining procedures. Reproduced from Ref. [5] with permission.

Table 3. List of pathology tools used for the detection of cancer.

Tool/modality	Description	Limit of detection	Applications	Reference
Histopathology	Examination of tissues under a microscope to identify disease.	Single cells	Tissue analysis for various cancers.	[50]
Cytology	Study of individual cells to detect abnormalities.	Single cells	Screening for cervical and other cancers.	[51]
Immunohistochemistry (IHC)	Use of antibodies to detect specific antigens in cells of a tissue section.	Protein expression levels	Determining cancer subtypes and prognosis.	[50]
Molecular pathology	Study of molecules within organs, tissues, or bodily fluids.	Varies by assay	Genetic mutations, gene expression.	[52]
Genetic testing	Analysis of DNA, RNA, chromosomes, proteins, and certain metabolites.	Single nucleotide changes	Hereditary cancer syndromes, targeted therapy decisions.	[52]
Liquid biopsy	A non-invasive test that detects cancer cells or their DNA in blood.	Circulating tumor DNA	Monitoring, early detection of cancer.	[51]
Tumor marker tests	Blood tests can help to identify the presence of certain types of cancer.	Varies by marker	Prognosis, monitoring treatment response.	[52]

5. Genomics and personalized cancer medicine

The field of cancer genomics has benefited immensely from AI-driven data analysis. Large-scale genomic datasets, encompassing information on genetic mutations, gene expression, and molecular pathways, have provided a wealth of information for understanding cancer biology and identifying potential therapeutic targets [53]. AI algorithms excel in identifying subtle genetic patterns associated with cancer predisposition, allowing for the identification of individuals at higher risk of developing specific cancers. Furthermore, AI-powered models enable the identification of biomarkers that predict treatment response and guide the selection of targeted therapies, leading to more effective and individualized treatment strategies [15,54–58]. As an example of AI's impact on cancer genomics, researchers have employed ML algorithms to analyze genomics data and identify driver mutations in cancer genomes [59]. These driver mutations play a crucial role in the initiation and progression of cancer. AI's ability to shift through vast genomic datasets has accelerated the identification of rare and previously unknown mutations that contribute to cancer development [60].

Additionally, AI has been pivotal in deciphering complex gene expression patterns that characterize different cancer subtypes [61]. By categorizing patients based on the unique molecular signatures of their tumors, AI algorithms assist in tailoring treatment regimens that align with the genetic makeup of the tumor and the patient's predicted response [62]. Similarly, multi-omics is an integrative approach that examines the datasets of various “omic” layers, such as genomics, proteomics, and metabolomics, to gain a comprehensive understanding of biological processes and disease mechanisms. This approach is pivotal in personalized medicine as it allows for the analysis of how genes, proteins, and other molecules interact within a cell or organism, and how these interactions are altered in disease states [63,64]. Recently, multi-omics and AI have been used for the advancement of personalized medicine, detecting novel subtypes, and predicting treatment responses. Wang et al. introduced AI to analyze multi-omics data from breast cancer patients. They found novel cancer subtypes with distinct therapeutic exposure, opening a new way for targeted therapies based on an individual's specific cancer biology condition. The combined power of multi-omics and AI holds immense promise for revolutionizing healthcare towards a more personalized and effective approach.

6. Clinical decision support systems in cancer detection

AI-driven clinical decision support systems have gained prominence in guiding treatment planning and patient management. These systems utilize patient data, including clinical history, imaging results, and molecular profiles, to assist oncologists in making informed decisions about treatment options [65]. ML algorithms analyze patient-specific data to predict treatment responses, adverse effects, and disease progression, facilitating personalized and adaptive treatment plans [66,67]. Such real-time insights optimize therapeutic efficacy and minimize unnecessary interventions, ultimately enhancing patient quality of life. Moreover, AI’s potential is not limited to primary diagnosis; it extends to image-guided interventions. AI-powered image registration and fusion techniques enhance the precision of minimally invasive procedures, enabling accurate targeting of tumors and reducing the risk of complications [68]. For instance, AI-driven navigation systems enhance the accuracy of needle biopsies and radiofrequency ablations, improving the success rates of these procedures [9]. These innovations underscore AI’s role in bridging the gap between diagnostics and treatment, revolutionizing the continuum of cancer care.

In addition to treatment decisions, AI aids in prognosis assessment. By analyzing multi-modal patient data, including imaging, clinical reports, and genomics, AI models can provide prognostic insights for cancer outcomes, helping clinicians understand disease trajectories and tailor follow-up strategies [69]. Furthermore, AI assists in the discovery of potential therapeutic targets by analyzing intricate interactions within molecular pathways and identifying druggable vulnerabilities in cancer cells [70]. Through integration with high-throughput technologies, AI expedites drug discovery and development, potentially leading to novel therapeutic agents with enhanced efficacy and reduced side effects [3].

The AI-assisted clinical decision support system can enhance the performance of screening mammography images in the identification of cancer and non-cancerous cells. Dembrower et al. identified that when AI is combined with radiologists, an increase of 21% is observed in the number of examinations with abnormal interpretation [71]. The study noted that AI and human experts can perceive different image features as cancer cells. Hence, the combination of AI and radiologists can increase the sensitivity of the detection of cancer [71]. Fan et al. explored the use of AI in detecting hematological cancers such as leukemia and lymphoma from digitalized images of peripheral blood films [72].

7. Challenges and future directions in the role of artificial intelligence in cancer detection

While the potential of AI in cancer detection is substantial, a lot of challenges persist in AI-driven healthcare systems. Ethical considerations, data privacy concerns, and algorithm bias necessitate vigilant oversight and collaboration among healthcare professionals, data scientists, and regulatory bodies [73,74]. The security and confidentiality of patients are major and challenging issues in AI-driven healthcare systems. The frequency of unauthorized access and data breaches has shown a significant spike in recent decades and can hurt this ecosystem. The guidelines need to be established by the concerned authorities across the globe, which should also lead to accountability at each level. Also, ethical concerns regarding the application of AI tools pose a serious issue in front of society. The recommendations made by the AI tools need to be critically evaluated by clinical experts before implementation for the best interests of the patients [75].

The major challenge of AI in cancer diagnosis is the lack of standardization of algorithms with data analysis and collection. It is very difficult to compare the results across different studies, which hinders the development of reliable algorithms. The requirement for transparent and interpretable AI models presents another difficulty [76]. The algorithms exhibit bias that, many times, gets amplified by using AI tools, which is a serious challenge in AI-driven healthcare systems. The AI algorithm that gets trained on some specific population does not necessarily perform best for other populations present in some different regions [77]. There can be several levels at which AI algorithms can be improved, such as data collection and preparation methods, model development and validation, model deployment in a clinical environment, types of patients, and regions of the deployment [78]. There is a requirement for more studies that discuss this challenging issue and suggest some level at which the biases in models can be accepted. The data collection methods favoring certain types of populations may also lead to bias in the model. It must be ensured that the training dataset of the ML model has representation from all populations to reduce the disparities in the result. The validation of results obtained from the model must be thoroughly examined across diverse classes or populations to reduce the bias in the model outcome.

For clinicians to trust AI models and use them in clinical decision-making, they must be able to explain how the models arrived at their diagnosis of cancer. The generalizability of AI algorithms across diverse patient populations and healthcare settings is crucial to ensure equitable access to AI-powered diagnostic tools [73,79]. Furthermore, efforts to enhance algorithm interpretability and address issues related to transparency and trust are imperative for widespread clinical adoption [80,81]. One major obstacle to AI research and algorithm development has been the absence of big, publicly available, well-annotated cancer datasets. Validation and reproducibility in cancer research are hampered by the absence of benchmarking datasets. Another difficulty is creating reliable algorithms that can manage complicated data [79]. The validation and reproducibility of AI-driven cancer research can be promoted by incorporating open data-sharing policies by various research facilities and institutions working across the globe on AI-based cancer detection. Collaborative research among doctors and the scientific community can lead to innovative solutions to the problem of cancer detection using AI tools. The domain of AI-based cancer detection faces several constraints such as regulatory compliance, inflexible healthcare systems, and difficulties in practical implementations. The absence of frameworks for the standardization of cancer-related health data also presents a significant obstacle in the development of AI models [79].

Despite several challenges and limitations, the use of AI in cancer detection has a bright future ahead. AI can, for instance, be used to evaluate vast volumes of data from many sources, such as imaging, proteomics, and genetic data, to find novel biomarkers for the diagnosis and treatment of cancer. AI is also capable of creating customized treatment programs according to a patient's individual genetic profile and medical background. Additionally, by lowering false positives and false negatives, AI can be used to increase the accuracy of cancer screening procedures like mammography and colonoscopy [82].

8. Conclusions

AI in oncology has catalyzed a paradigm shift, guiding in a new era of cancer detection, diagnosis, and treatment. Its applications across various domains such as radiology, pathology, genomics, and clinical decision–support systems hold immense promise in reshaping patient care and outcomes. Beyond just augmenting human capabilities, AI is fundamentally modifying the healthcare landscape by enabling precise and efficient analysis of medical images, genetic intricacies, and treatment responses. These capabilities not only rationalize the diagnostic process but also revolutionize treatment strategies. AI-powered risk-prediction models and advanced imaging techniques enable clinicians to detect cancer at its earliest stages, significantly improving survival rates and patient prognosis. Moreover, the arrival of precision medicine driven by AI allows the customization of interventions based on individual genetic and molecular profiles, optimizing treatment efficacy while minimizing adverse effects and enhancing overall quality of life. However, to fully realize the potential of AI in clinical practice, several challenges must be addressed, including ensuring data privacy, mitigating biases in algorithmic decision-making, and maintaining transparency and accountability. As AI technologies continue to evolve, the implementation of explainable AI, robust validation protocols, and ethical guidelines will be pivotal in fostering responsible and widespread adoption of AI-powered solutions in oncology.

Collaborative efforts among healthcare stakeholders, data scientists, and regulatory bodies are essential for advancing AI’s role in cancer detection and facilitating patient-centered care. In conclusion, the integration of AI in cancer detection represents a transformative moment in healthcare. By leveraging AI to enhance early diagnosis, tailor treatment strategies, and improve patient outcomes, we can redefine the approach to cancer care and move towards a future where timely interventions and personalized treatments are the standard of care.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare no conflicts of interest.

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