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Harnessing artificial intelligence for theragnostic applications: Current landscape and future directions

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Abstract In the area of theragnostics, the use of artificial intelligence (AI) is supporting personalised medicine methods that merge therapeutic and diagnostic techniques, which is causing the sector to undergo a transition. An analysis of the historical backdrop, current condition, and promise of artificial intelligence-enhanced theragnostic systems is presented in this article. We investigate the underlying ideas of artificial intelligence, such as machine learning, deep learning, and neural networks, as well as their applications in a variety of medical fields, including cancer, pathology, medical imaging, cardiology, hypertension control, and diabetes management. The ability of artificial intelligence systems to integrate a wide variety of information, recognise trends, and enable real-time decision-making and patient monitoring all illustrate their competency. It is possible that personalised digital twins, which make use of adaptive learning algorithms and dynamic virtual models, might be used to optimise treatment regimens and anticipate the course of illness. Important prospects for the advancement of biomedical research and personalised therapy are presented by biochip technology that is driven by artificial intelligence. This technology includes gene chips, organ-on-a-chip systems, and biosensors. However, there are a number of obstacles that must be overcome before artificial intelligence can be effectively used in theragnostics. These obstacles include data security, privacy, algorithmic biases, legal frameworks, and patient acceptability. It is vital, in order to realise the full potential of AI-driven theragnostic techniques, to address these constraints by means of extensive validation, diversified datasets, explainable artificial intelligence, and clear communication. It is anticipated that the synergistic combination of artificial intelligence and theragnostics will revolutionise precision medicine as research continues to advance. This will make it possible to make more accurate diagnoses, achieve more tailored therapeutics, and achieve better patient outcomes.

Keywords: machine learning, deep learning, personalized medicine, targeted therapies, multi-omics data

1. Introduction

The combination of therapeutic and diagnostic modalities has begun in the area of nuclear medicine, where it has been applied for many decades, notably in the treatment of benign and malignant thyroid diseases (Langbein et al., 2019; Sólnes et al., 2020). The word "theragnostic" was first incorporated into medical parlance in 1998 when John Funkhouser created a test to monitor the effectiveness of a new anticoagulant medication, officially making this integrated diagnostic-therapeutic strategy (Langbein et al., 2019). The use of theragnostic techniques has dramatically increased over time, especially in the context of cancer. In recent years, this integrated diagnostic-therapeutic strategy has been effectively used for a broad variety of cancers, with neuroendocrine tumours emerging as a prominent example (Langbein et al., 2019; Sólnes et al., 2020). The NETTER-1 trial, focused primarily on midgut neuroendocrine tumours, has provided a foundation to support the utilisation of peptide receptor radionuclide therapy in tumours of diverse origins, including bronchial and hindgut NETs, as evidenced by retrospective data suggesting potential benefits (Bilgin et al., 2024). The merging of theragnostics and developments in artificial intelligence has opened new vistas in precision medicine. The capacity of AI to assess and synthesise multiomics data is crucial in boosting the customisation of theragnostic techniques (Sezgın, 2023). The combination of AI and theranostics strives to improve patient selection, optimise treatment planning, and continually analyse and adjust therapy success (Zhang et al., 2014). Comprehending the historical backdrop and technical breakthroughs that have created the field of theragnostics is vital for optimising its therapeutic relevance as the discipline continues to expand.

2. Principles Underlying Artificial Intelligence

Before investigating how AI is employed in the field of theragnostics, it is crucial to grasp some key terminology first. AI is a broad notion that incorporates all sorts of algorithms that help robots understand and solve issues as people do (Bilgin et

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al., 2024; Currie et al., 2019). With AI, there are more minor aspects, such as machine learning, deep learning, and neural networks (McBee et al., 2018). The more complex these algorithms are and the more significant the datasets employed are, the more accurate the findings will be, particularly when tackling challenging jobs (McBee et al., 2018). Machine learning, a prominent AI technology, uses structured data, which means that the data are arranged neatly, such as numbers or text entries with names and dates, to discover trends and complete tasks. This approach is distinct from other AI systems that can employ alternative kinds of data or modes of learning (Currie & Rohren, 2020). Unstructured data, such as photographs or text, do not have a fixed format or structure, making them more challenging to investigate. Even though this type of data delivers more context and depth, processing it requires more complex algorithms than what is utilised in machine learning (Currie et al., 2019). Neural networks, which are a component of machine learning, are formed of linked nodes that operate like brain neurons (Sailaja et al., 2021). These networks contain an input layer, hidden layers in the middle, and an output layer. This tiered structure helps process data in phases. Adding additional layers and utilising more data may enhance the outcomes from these networks. There are several varieties of neural networks, each built for distinct types of data and activities. One example is convolutional neural networks, which employ complex arithmetic to examine and comprehend visual data, showing significant promise in radiography (Zhang et al., 2020). Deep learning, which is the most potent type of AI, employs complicated algorithms and extended training sessions to detect patterns in enormous volumes of data. It combines several neural networks to carry out challenging tasks with great accuracy (Tang et al., 2018). The name "deep" alludes to the multiple layers in these networks, which enables them to solve challenging issues. Unlike typical machine learning, which employs structured data, deep learning can operate with unstructured data without requiring human input (Bilgin et al., 2024; Minar & Naher, 2018). Since much of the data is unstructured, deep learning is projected to influence the IT sector substantially. Figure 1 shows a simple mind map displaying the categorisation of the ML models and their present uses.

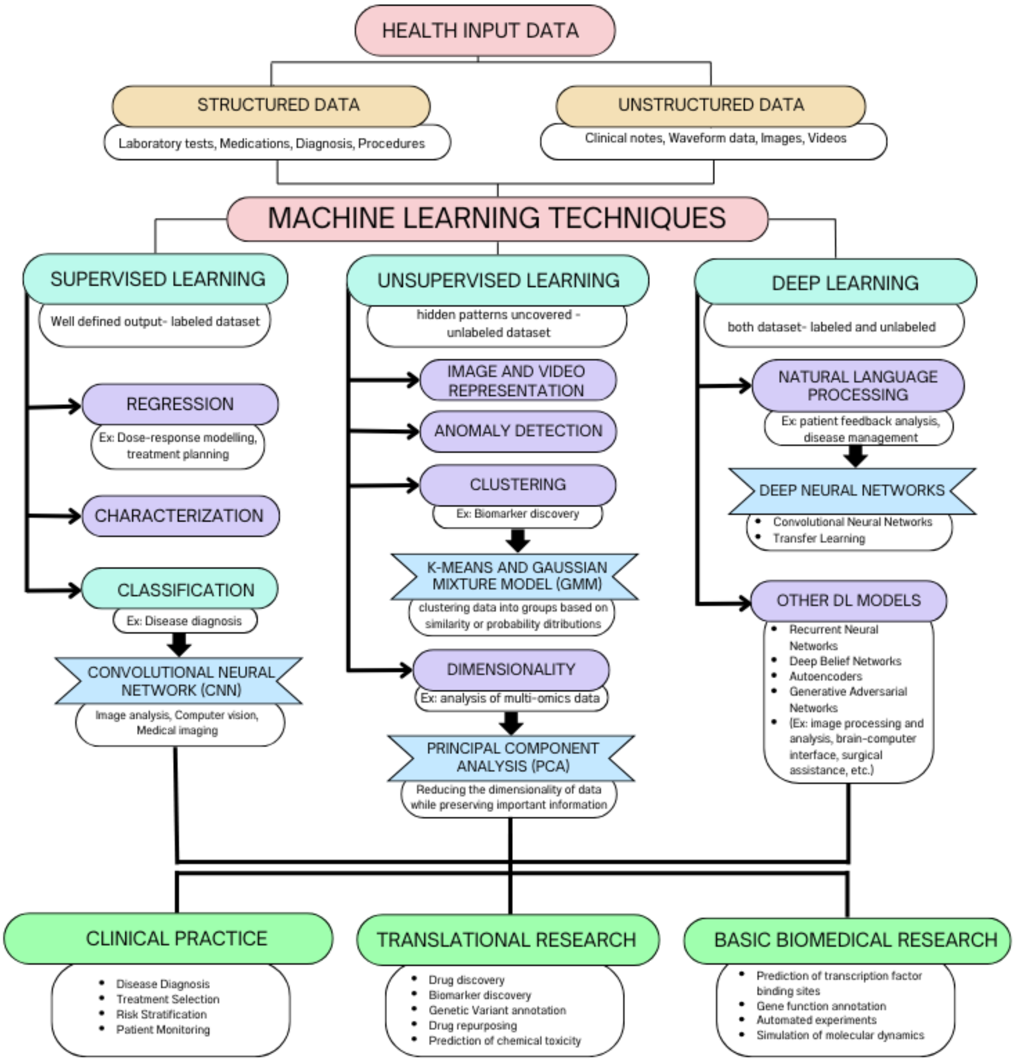

Figure 1 A simplified mind map showing the classification of ML models and their current applications. *Source:* (K. W. Johnson et al., 2018; Rashidi & Chen, 2023; Sharma et al., 2024, 2024; Toh et al., 2019).

3. Artificial Intelligence Applications in Theragnostic Advancements

The evolution of molecular imaging technologies has produced a vast volume of imaging data, making it essential to build new tools and software to interpret and comprehend this information. Since the FDA authorised its first AI-powered Medical gadget in 1995, artificial intelligence has become increasingly engaged in healthcare. To date, more than 950 AI and machine learning algorithms have been certified by authorities, mainly in radiology and cancer. Table 1 displays the distribution of FDA-approved AI and machine-learning medical devices across various medical sectors, spanning the period from 1995 to June 2024 (FDA, 2024). Importantly, none of these authorised systems are primarily geared against theragnostic.

Table 1 Distribution of FDA-approved AI and machine learning medical devices across different medical fields, covering the period from 1995--June 2024.

Speciality	Field of AL/ML	Number of AI/ML hanced medical devices
Anesthesiology	Ventilatory Effort Recorder	5
	Abnormal Breath Sound Device	1
	Ultrasound Guided Nerve Block Assist	1
	Anesthesiology's adjuvant pain measurement tool	1
	Spirometer, Diagnostic	1
Anesthesiology Total		9
Cardiovascular	Computer, Diagnostic, Programmable	17
	Stethoscope, Electronic	7
	Coronary Vascular Physiologic Simulation Software	7
	Event recorder, implanted cardiac device (with the ability to detect arrhythmias)	6
	Electrocardiograph	6
	Medium-Term Predictive Adjunctive An indicator of cardiovascular disease	5
	Physiological, patient, and monitor (without alarms or detection of arrhythmias)	5
	Transmitters And Receivers, Electrocardiograph, Telephone	5
	Program for Optical Camera-Based Pulse, Heart, Breathing, and/or Respiratory Rate Assessment	4
	Over-the-Counter Photoplethysmography Evaluation Application	3
	Decision Point-Based Adjunctive Hemodynamic Indicator	3
	Multivariate Vital Signs Index	2
	Notification Program Built on Machine Learning with a Lower Ejection Fraction	2
	Adjunctive Predictive Cardiovascular Indicator	2
	Physiological, patient, and monitor (with alarms or arrhythmia detection)	2
	Angiographic Coronary Vascular Physiologic Simulation Software	2
	Electrocardiograph, Ambulatory, Equipped with an Analysis Software	1
	Pulmonary Hypertension Machine Learning-Based Notification Software	1
	Plethysmograph, Impedance	1
	Radio waves, physiological signals, transmitters, or receptors	1
	Recorder, Magnetic Tape, Medical	1
	Intravascular Bleed Monitor	1
	Optical Coherence Tomography and Imaging	1
	Coronary Artery Disease Machine Learning-Based Notification Software	1
	Probe, Blood flow, Extravascular	1
	Adjunctive Heart Failure Status Indicator	1
	Atrial Fibrillation Risk Prediction Machine Learning-Based Notification Software	1
	Detector And Alarm, Arrhythmia	1
	Electrocardiograph, Ambulatory (Without Analysis)	1
	Military Use of an Adjunctive Haemodynamic Indicator With Decision Point	1
	cardiovascular machine learning-based notification software	1
	Oximeter	1

	Over-the-Counter Electrocardiograph Program	1
	Software and hardware components for measuring respiratory and heart rates using optical cameras	1
	Adjunctive Epicardial Vascular Physiologic Status Indicator	1
	A program for simulating therapeutic cardiovascular implants	1
Cardiovascular Total		98
Clinical Chemistry	Indicator Method: Albumin or Protein (Non-Quant, Urinary)	2
	System, Test, Blood Glucose, Over The Counter	2
	Adjustment Calculator for Insulin Pump Therapy for Medical Practitioners	2
	Enzymatic Method, Creatinine	1
	Method, Enzymatic, Non-Quantitative, Urinary Glucose	1
Clinical Chemistry Total		8
Dental	Orthodontic Software	2
	Dental Navigation System	1
Dental Total		3
Ear Nose & Throat	Rhinoanemometer (Measurement Of Nasal Decongestion)	1
	Stereotaxic Ear, Nose, and Throat Instrument	1
Ear Nose & Throat Total		2
Gastroenterology-Urology	Gastrointestinal Lesion Software Detection System	10
	Monitor, Extracellular Fluid, Lymphedema, Extremity	2
	Radiofrequency, physiological signals, transmitters, and receivers	1
	Adjunct Monitor, Protein Calorie Malnutrition	1
	Gastroenterology-Urology Total	14
General and Plastic Surgery	System, Optical Coherence Tomography (Oct), Imaging	2
	A System for Analysing Images to Estimate External Blood Loss	2
	System, Surgical, Computer Controlled Instrument	1
	Oximeter, Tissue Saturation	1
	General and Plastic Surgery Total	6
General Hospital	Calculator, Drug Dose	2
	Thermometer, Electronic, Clinical	1
	Accessories, Pump, Infusion	1
General Hospital Total		4
Haematology	Device, Automated Cell-Locating	10
	Counter, Differential Cell	4
	Semen Analysis Device	2
	Counter, Urine Particle	1
	technique for detecting genetic variants and evaluating health risks	1
Hematology Total		18
Immunology	Autoimmune disease, diagnostic software, and the K-Nearest Neighbour algorithm	1
Immunology Total		1
Microbiology	System, Identification of Microorganisms, Mass Spectrometry, Maldi Tof, and Cultured Isolates	2
	Identification and Ast Kit for Positive Blood Cultures	1
	Multiplex screening for Influenza A and Influenza B Nucleic Acids	1
	Microbial Colony Image Assessment System	1
Microbiology Total		5
Neurology	Neurological Stereotaxic Instrument	5
	Software for Automatic Polysomnograph Event Detection Using Electroencephalography	5
	Oculomotor Assessment Aid for Adjunctive Interpretation of Brain Injury	4

	Software for Automatic Event Detection in Full-Montage Electroencephalograms	4
	Assessment Tool for Adjunctive Interpretive Electroencephalography of Brain Injury	4
	Electrode, Cutaneous	4
	Diagnosing Autism Spectrum Disorder in Children	3
	System for Monitoring Seizures Based on Physiological Signals	2
	Transducer, Tremor	1
	Orthopedic Stereotaxic Instrument	1
	Device, Sleep Assessment	1
Neurology Total		34
Obstetrics and Gynecology	Embryo Image Assessment System, Assisted Reproduction	1
Obstetrics and Gynecology Total		1
Ophthalmic	Diabetic Retinopathy Detection Device	7
	Camera, Ophthalmic, Slit-Scanning	1
	System, Image Management, Ophthalmic	1
	Nystagmograph	1
Ophthalmic Total		10
Orthopedic	Orthopedic Stereotaxic Instrument	4
	Knee Arthroplasty Implantation System	1
Orthopedic Total		5
Pathology	Tissue of Origin for Malignant Tumour Types, Software, and Similarity Score Algorithm	4
	Whole Slide Imaging System	3
	A gadget that uses software algorithms to help users with digital pathology	1
Pathology Total		8
Physical Medicine	Device, Sensing, Optical Contour	1
Physical Medicine Total		1
Radiology	System, Image Processing, Radiological	142
	Application for Automatically Interpreting Radiological Images	125
	X-ray, Tomography, Computed	73
	Imaging, Pulsed Doppler, Ultrasonic	64
	Nuclear Magnetic Resonance Imaging	63
	Application for Computer-Assisted Triage and Notification in Radiology	55
	Computer-Aided Radiological Prioritisation Program for Lesions	34
	Image Processing Software For Radiation Therapy	31
	Radiation Therapy Treatment	24
	Software for Computer-Aided Detection and Diagnosis of Cancerous Lesions	28
	Analyser, Medical Image	18
	System, Tomography, Computed, Emission	16
	Application for Radiological Computer-Assisted Fracture Detection and Evaluation	6
	System, Imaging, Pulsed Echo, Ultrasonic	6
	Detection Assisted by Computers, Lung Computed Tomography System	6
	Fluoroscopic Interventional X-ray System	5
	Using Artificial Intelligence to Guide Gathering Images and/or Optimisation	16
	Imaging Companion Diagnostic for Deferasirox Liver Iron Concentration	2
	Application for Analysing Radiological Images for Setting up and Assessing Ablation Therapy	2
	Accelerator, Linear, Medical	2
	Nuclear Magnetic Resonance and Emission Computed Tomography Combined in a Tomographic Imager	1
	radiology software for opportunistic evaluation of low bone mineral density	1

	System, X-ray, Mobile	1
	Quantitative imaging software with a change control strategy based on radiological machine learning	1
	Densitometer, Bone	1
Radiology Total		723
Grand Total		950

Source: FDA, 2024.

4. Mechanisms of Integration and Application

4.1. Data integration and analysis

AI is able to integrate heterogeneous information and identify patterns and insights that conventional techniques may fail to detect. This skill involves the integration of electronic health records and laboratory data to maximise patient care, allowing healthcare practitioners to adapt therapies depending on individual requirements and illness severity (Bennett & Hauser, 2012). Furthermore, the application of radiometric data intensifies this integration by translating medical pictures into high-dimensional, data-rich forms. AI algorithms may automate lesion segmentation and speed image capture, therefore increasing diagnostic accuracy and personalising treatment planning (Ladbury et al., 2023).

4.2. Real-time decision-making and patient monitoring: artificial intelligence-assisted remote monitoring

AI-enabled theranostic systems may facilitate real-time decision-making and patient monitoring. By continually assessing patient data and tumor features, AI models may enable healthcare practitioners to modify treatment strategies as clinical circumstances develop, ultimately maximising patient outcomes. This dynamic flexibility is critical for successful cancer therapy, allowing early interventions on the basis of continuing evaluations of disease progression and treatment response. AI based remote monitoring employs numerous approaches to assess fluid levels in the body. For example, it may research how fluid affects voice cords, utilise 3D-image sensors to quantify leg swelling or use low-power electromagnetic impulses to estimate lung fluid, such as chest CT findings. Another option is seism cardiography on smartphones, which measures heart vibrations to detect heart failure patients (Rao et al., 2018; Gupta et al., 2020; Wheatley et al., 2020). Table 2 highlights the various limits in clinical assessment and how AI might assist in fixing such shortcomings.

In Apple Heart Research, 419,297 participants without atrial fibrillation utilised their smartwatches to monitor heart rhythms. Although they consented to use their watches, the positive predictive value of alerts was only 0.84, suggesting numerous false positives (Pérez et al., 2019). While smartwatches show promise for health monitoring, scaling them up should be performed carefully. One key problem is that gadgets from various manufacturers might operate exceptionally differently. For example, many ambiguous ECG readings are generated by noise; however, noise-adapted models could increase accuracy (Abu-Alrub et al., 2022). Research of 60,629 patients in Belgium revealed that screening for concealed arrhythmias led to more persons taking blood thinners, but it did not substantially modify risk management for atrial fibrillation (Khunte et al., 2023). Widespread screening promotes awareness and stimulates prompt medical visits, but the low incidence of these illnesses in healthy people might result in numerous false positives (Gruwez et al., 2023). New monitoring devices that employ various technologies to track health are being developed. For example, smartwatches may monitor cardiac rhythms, research frailty, and record precordial lead signals (Cheung et al., 2018; Al-Alusi et al., 2019). Additionally, AI-powered devices without cuffs are being studied for monitoring blood pressure via photoplethysmography (Mannhart et al., 2023; Mohammadi et al., 2022).

Table 2 Possible limitations in clinical evaluation and how AI can help rectify those limitations.

References	Examination	Limitations while using conventional methods	Automation to remove limitations	Inference
(Fan et al., 2023; Kraus et al., 2022; Mizuguchi et al., 2024)	Frailty evaluation	• Subjective • Assessment conducted in the clinic could not represent long-term patterns.	Standardised frailty measurements are sought after by ML-guided gait sensors or smartwatches.	Helpful supplemental instruments for assessing life quality and calculating the risk/benefit ratio of specific treatments, such as anticoagulation.
(Joung et al., 2023, 2023; Schutte et al., 2022; Sel et al., 2023)	Blood pressure (BP)	• A single moment in time that might not depict long-term patterns, latent illness, or paroxysmal events	Wearable blood pressure monitors without cuffs for community-wide longitudinal monitoring	-Observation in real time -Observation over time -Early intervention can be provided.

(Khurshid et al., 2023; Lubitz et al., 2022; Perez et al., 2019)	Pulse Rate assessment		Wearable technology for community activity and rhythm monitoring in real time	
(S. Lin et al., 2020; Matsui et al., 2019)	Clinical examination of signs	• Subjective and frequently overlooked (xanthomas, for example) • Inaccurate (like Frank's sign)	Applying CNN-based computer vision models to images (such as faces or other) may indicate a risk of coronary artery disease.	Restricted by dubious generalizability among various racial and ethnic groups.
(Dunn et al., 2023; Poplin et al., 2018; K. Zhang et al., 2021)	Fundoscopic examination	• Rarely performed • Steep learning curve	At the point of care, retinal picture capture with direct inference to reveal concealed CV labels is possible thanks to computer vision models tailored for smartphones.	Improved methodology for the detection of cardiovascular disease.
(Breidthardt et al., 2018; Lam Po Tang et al., 2018)	Jugular venous pulsation (JVP)	• Poor agreement • High interrater variability36	Digital camera or photoplethysmography-based technologies to automatically characterise pulsations in the jugular vein	The sensitivity and specificity for detecting CVP over 5 mmHg are 69% and 28%, respectively.
(Brodovicz et al., 2009)	Adverse lower limb oedema	• Subjective assessment • Frequently difficult to compare to baseline	Image comparison to customised anatomical models for longitudinal tracking using computer vision	give individualised, observer-independent oedema measurements, as these are currently constrained by inadequate interrater agreement.
(Andersen et al., 2022)	Volume status examination	• Often, evaluation is based on a combination of physical examination and history.	Adding other easily accessible data, such as speech-based analytics, to weight monitoring and physical examinations	
(Bachtiger et al., 2022; Chorba et al., 2021; Luo et al., 2022; Narang et al., 2021)	Auscultation	• Variability between raters • A steep learning curve • Accuracy that is not ideal • Inequalities in diagnosis made worse by limited access to ECG	Use digital stethoscopes or phonocardiography applications that are compatible with smartphones for uniform recording and analysis.	Helpful in standardising the collection and interpretation of data. Three out of four recordings were of high quality, and more than four out of five users were able to get at least one recording using a smartphone-adapted program.
			ECG-enabled stethoscopes can support diagnostic reasoning by adding AI-ECG tools to auscultation results.	When compared to conventional treatment, AI-ECG-based screening led to a 32% increase in the diagnosis of LVSD without appreciably raising the rates of echocardiography referral.
			Wearable ultrasonic imager patches in conjunction with point-of-care ultrasonography to	This emerging technology might provide effective phenotyping in

		augment auscultation findings	ambulatory settings through subsequent. iterations that adhere to a procedure as straightforward as connecting an ECG lead.

AI-driven theranostics might help physicians make real-time choices and monitor patients, but there are questions about their hazards and limits. Continuously studying patient data and tumours does not necessarily lead to improved treatment recommendations, and depending too much on AI might lead to bad results (Rafiq et al., 2020). The ability of AI to adapt swiftly in cancer treatment can potentially make providing consistent, evidence-based therapy more challenging since the algorithms might have biases or inconsistencies (Crigger et al., 2022; Challen et al., 2019). It is vital to rigorously evaluate and verify these technologies to ensure that they help, rather than damage, cancer therapy and patient care.

4.3. Personalised digital twins: Harnessing dynamic, data-driven patient profiles for improved disease monitoring

With the use of adaptive learning algorithms, AI may enhance the way standard metrics are employed for tracking treatment (Lorenzo et al., 2024). Many studies have demonstrated that positron emission tomography (PET) readings and their variations throughout therapy may provide important information about how a disease is developing and how successful the treatment is. For example, in prostate cancer, changes in tumor size are utilised as indicators to measure how effectively radiation functions (Bilgin et al., 2024). Various AI systems provide virtual consultations, aiding both physicians and patients across diverse medical specialities and enhancing the therapeutic experience. For example, Tempus Labs, an AI assistant, looks at patient data to construct a thorough profile and delivers real-time individualised therapy suggestions to aid in decision making. By combining electronic health records and lab data, AI algorithms assist in enhancing cancer treatment by prioritising patients and advising healthcare practitioners on follow-ups and therapies on the basis of individual patient requirements (Theranostics et al., n.d.). This strategy aims to utilise resources effectively and optimise patient outcomes. Digital twins, which are dynamic virtual models, mirror real-life objects or systems via real-time data, simulations, and machine learning. In healthcare, these digital twins operate as virtual representations of patients, helping clinicians make judgments (Ali et al., 2024; Vallée, 2023). They contain diverse data sources, such as medical records, photos, and genetic information. Unlike conventional models, digital twins may learn and adapt to changes over time, enabling a novel approach to generate tailored treatment plans and comprehending how a disease may proceed (Foundational Research Gaps and Future Directions for Digital Twins, 2023; Chaudhuri et al., 2023; Sun et al., 2023). Figure 2 shows the concept of digital twins.

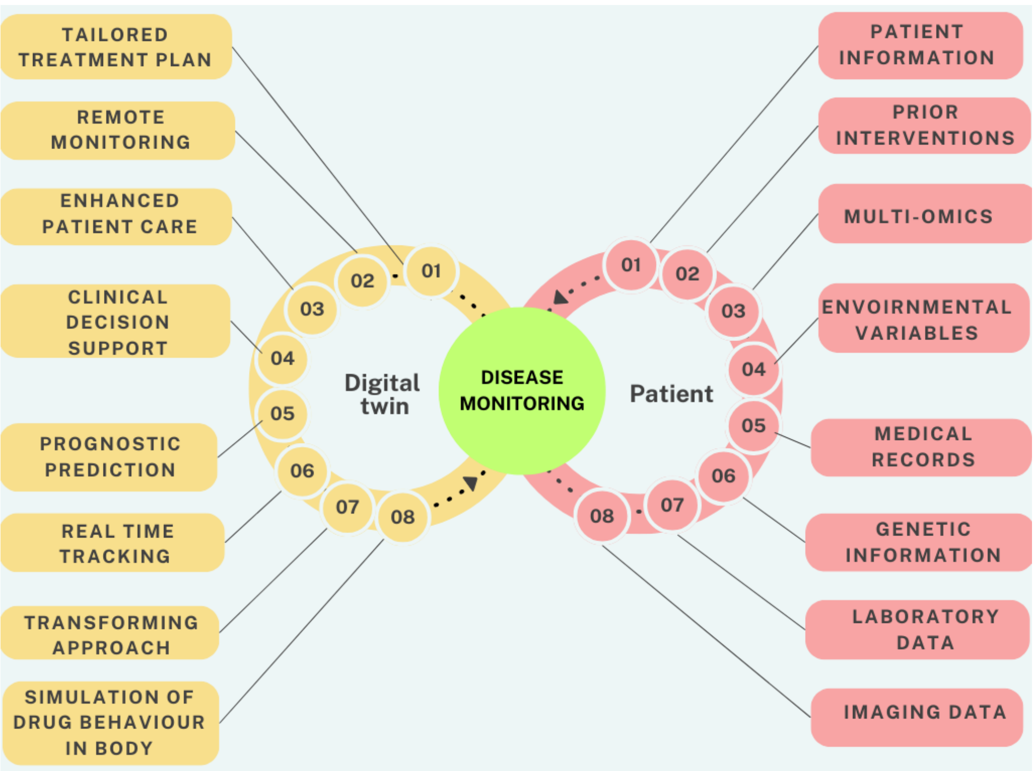

Figure 2 The concept of digital twins. *Source:* (Foundational research gaps and future directions for digital twins, 2023; Chaudhuri et al., 2023; Sun et al., 2023).

4.4. Curate: AI in optimising personalised medicine

Personalised precision medicine attempts to enhance how AI is used to determine therapies, helping clinicians identify the optimum medicine for each patient. The quadratic phenotypic optimisation platform (QPOP) technique selects tailored medication combinations and beginning dosages, whereas CURATE. AI changes dosing during therapy depending on a patient's evolving profile (Blasiak et al., 2019). These strategies function without having extensive data on how medications interact or how they are digested in the body, and they may reveal novel insights relevant to each system. In a complete clinical implementation of personalised precision medicine, a patient's biological sample, such as blood or a tumor, is first examined via QPOP to determine the optimum medicine combination. Then, CURATE. AI would oversee dosage modifications for that patient throughout therapy. This technique allows for a highly tailored strategy, which involves picking the medications, establishing their starting dosages, and controlling dosing modifications over time. As QPOP and CURATE. AI continues to be validated for numerous clinical diseases, and this scenario is becoming more feasible (Polasek et al., 2018).

CURATE. AI has previously proven results in a pilot trial for metastatic castration-resistant prostate cancer, where it helped modify combination treatment for individual patients (Kee et al., 2019). This opens the door for CURATE. AI can be used in other areas, such as treating multiple myeloma and maintaining immunosuppression. Similarly, QPOP has been demonstrated in various in vivo trials for illnesses, including cancer, TB, and multiple myeloma (Pantuck et al., 2018). As further clinical studies offer real-world evidence, both CURATE. AI and QPOP are on pace to be authorised for new purposes and obtain regulatory clearance for broader clinical usage. The expanded adoption of personalised precision medicine might offer considerable improvements to healthcare, lessening the overall pressure on health systems. Early accomplishments of CURATE. The ability of AI and QPOP to improve patient outcomes implies that they have significant potential for the future (Kee et al., 2019).

AI-assisted biochip technology for biomedicine combines various domains, including semiconductor microfabrication, electronics, nanotechnology, biochemistry, and biology (Rodoplu, 2024). These tiny devices can be used to analyse or work with biological systems, molecules, or organisms for various medical uses, such as DNA or gene chips for diagnosing diseases, wearable or implantable biosensors, drug delivery systems, intelligent implants, brain chips, lab-on-a-chip, and organ-on-a-chip platforms (Rodoplu, 2024). Integrating artificial intelligence into biochip technology may make these devices more accurate, enhance decision-making, and add customisable capabilities (Cuschieri et al., 2022).

Biosensors are devices that employ a biological component, such as an enzyme or antibody, paired with a transducer to detect a material and transform that detection signal into a detectable electrical signal (Wu et al., 2024). Biochips may also operate as small biosensors that swiftly detect viruses, disease indicators, contaminants, and other biochemicals (Cui et al., 2020). They are utilised for diverse reasons, such as DNA chips for genomics, protein arrays for proteomics, and systems that research ion channels (Hassan et al., 2020). Other uses include single-cell platforms for identifying illnesses, lab-on-a-chip systems for assessing medication efficacy, and point-of-care testing for distant areas (Caoili et al., 2006). Gene chips, or DNA microarrays, are key instruments in molecular biology research. They comprise tiny DNA patches placed on a solid surface, enabling the study of thousands of genes at once. These methods assist in investigating gene regulation, locating illness indicators, and detecting infections (Liu & Wang, 2023). Gene chips are highly valuable in customised medicine, especially for identifying complex illnesses such as drug-resistant TB, which is a major global health concern owing to the sluggish and intricate nature of standard diagnostics (Caws & Drobniewski, 2001). Additionally, organ-on-a-chip (OOC) systems replicate biological processes in a controlled microenvironment, which is valuable for research and testing medicines (Zhang & Qiao, 2022). These systems leverage 3D tissue architecture and realistic circumstances, transcending the limits of simpler 2D models. They assist in reproducing complicated biological activities and are essential in medication development and research (Ortíz et al., 2020).

Biomedical electronic devices, such as brain implants, bioelectronic actuators, and neurostimulation chips, can detect and deliver electrical impulses to tissues, enabling therapeutic alternatives (Deng et al., 2023). Brain-chip technology is effective for recovering missing sensations or movement, controlling external devices, and even increasing cognitive ability (Robinson et al., 2019). Advances in conductive hydrogels have enhanced brain–computer interfaces (BCIs) by improving their flexibility and dependability. These hydrogels carry electricity and can connect better with tissues; however, when biochips are attached to wet, moving tissues remains challenging owing to weak bonding forces (Parastarfeizabadi & Kouzani, 2017). Researchers have constructed flexible, self-adhesive hydrogels employing ingredients such as polydopamine-coated graphene oxide and Fe^{3+} ionic cross-linkers. These advancements aid in activating and recording the neuromuscular system, helping regenerative medicine (Gutiérrez-Martínez et al., 2020). However, difficulties, including long-term compatibility and the hazards of surgery, still need to be solved (Altyar et al., 2022). Researchers are researching methods to increase the effectiveness of BCI systems, such as improving communication speeds (Altyar et al., 2022).

5. AI in Cardiology

Cardiovascular illnesses are among the most significant health challenges worldwide, causing approximately 17 million deaths per year (the top 10 causes of death, 2020). Machine learning (ML) is being utilised in cardiology and has positive outcomes. In cardiac imaging, ML helps automatically generate scores, detect distinct illness patterns, assess heart function, and map the heart's anatomy (Acero et al., 2020); Seetharam et al., 2020). This leads to improved diagnosis, risk assessment, and monitoring of cardiac diseases. Similarly, in electrocardiography, ML may identify abnormalities such as arrhythmias and latent heart malfunction early, which means that patients can receive prompt treatment and improve outcomes. Table 3 highlights the possible use of artificial intelligence applications for the detection of cardiovascular disorders via machine learning.

Table 3 Potential use of artificial intelligence applications for the diagnosis of cardiovascular diseases via machine learning.

Method	Aim	AI algorithm	Interpretation	Reference
Imaging	To view congestive heart failure's features on a chest imaging scan	Deep neural network	AUC was 0.82	(Seah et al., 2019)
Electrocardiogram	To recognise an arrhythmia on an ECG automatically	Deep neural network	98.5% is the correct recognition rate, with 92% accuracy	(Isin & Ozdalili, 2017)
Imaging	Existing echocardiographic findings can be used to estimate the area of the aortic valve without measuring the left ventricular outflow tract.	Multidimensional clusters	AUC was 0.95 and AUPRC: 0.73	(Playford et al., 2018)
Imaging	Automated differentiation between athletes' natural hypertrophy and hypertrophic cardiomyopathy	-Artificial neural networks -random forests -support vector machines	Sensitivity was 87% and overall specificity was 82%	(Narula et al., 2016)
Electrocardiogram	To determine if left ventricular systolic dysfunction is asymptomatic	Convolutional neural network	AUC was 0.93, Sensitivity was 86.3% Specificity was 85.7% and Accuracy was 85.7%	(Attia et al., 2019)
Imaging	View the echocardiography categorisation	Neural network	Accuracy was 97.8%	(Madani et al., 2018)
Risk assessment	To determine the prognostic characteristics of heart failure individuals who have preserved ejection fraction	Cluster analysis	Heart failure and preserved ejection fraction may be predicted by the lower left ventricle's systolic reserve.	(Przewlocka-Kosmala et al., 2019)
Risk assessment	To assess cardiovascular risk in individuals who do not exhibit any symptoms	-AdaBoost -Random Forest -Neural Network -Support Vector Machines -Gradient Boosting	AUC was 0.724	(Alaa et al., 2019a)
Electrocardiogram	Hyperkalaemia screening in chronic renal disease patients	Convolutional neural network	AUC was between 0.853 and 0.883	(Galloway et al., 2019)
Imaging	Segmenting LV automatically via cine magnetic resonance imaging	Deep neural network	fared better than manual segmentation.	(Ngo et al., 2017)
Risk assessment	To determine the hypertrophic cardiomyopathy risk of ventricular arrhythmia	-Logistic regression -Naıve bayes -Decision tree -Random Forest	AUC was 0.83, sensitivity was 0.73, and specificity was 0.76.	(M. Bhattacharya et al., 2019)

Risk assessment	To find within the hospital cardiac arrest and death without trying to revive	Deep neural network	AUC was 0.85 and AUPRC was 0.044	(Kwon et al., 2018)
Risk assessment	To forecast the duration of cardiac patients' hospital stays	-Artificial neural network -Random Forest -Vector machine support -The Bayesian network	With sensitivity, Random Forest fared better than the other models: 80% 80% accuracy and 0.94 AUC	(Daghistani et al., 2019)
Imaging	To identify and categorise the delayed improvement pattern in the heart	Convolutional neural network	Accuracy was 87.2	(Ohta et al., 2019)
Imaging	Completely automated measurement of LV from cine MR and assessment of its effectiveness in a multicenter and multivendor environment	Convolutional neural network	1.1 ± 0.3 mm was the average perpendicular distance compared to manual analysis.	(Tao et al., 2019)
Risk assessment	To predict heart failure patients' 30-day all-cause readmission rate	-Logistic regression -Poisson regression -Random Forest -Boosting	Compared to traditional statistical techniques, Random Forest fared better.	(Mortazavi et al., 2016)
Imaging	Without first segmenting coronary artery calcification, the Agatston score is calculated through a nonenhanced chest CT scan.	Convolutional neural network	0.932 is the Pearson correlation coefficient between the test set's calculated scores and the reference standard.	(Cano-Espinosa et al., 2018)

ML models have demonstrated considerable promise in changing how clinicians evaluate cardiovascular risks and forecast health outcomes. By examining vast datasets, these algorithms may identify complicated patterns that clinicians overlook, enabling more tailored and precise forecasts of risk and outcomes (Li et al., 2024). Additionally, ML is beneficial in genomics because it helps scientists comprehend gene functions and the relationships between genes and physical features. This may provide crucial insights into how illnesses operate and aid in the generation of tailored therapies (Moulik et al., 2020).

Despite these advantages, limitations remain in the application of ML in cardiology. Training ML models requires massive, high-quality datasets, and there is a danger of overfitting when the model becomes too particular to the data it was trained on and does not perform well on fresh data. Additionally, many ML algorithms act like a "black box," meaning that it is difficult for physicians to grasp how they work, which might make them reluctant to trust or employ these technologies (Cuocolo et al., 2019; Krittanawong et al., 2017). Even with these obstacles, the FDA has already authorised various ML algorithms for medical applications, notably in cardiology and radiology, suggesting that this technology is becoming increasingly recognised in healthcare. As research progresses, it is believed that ML will lead to even more accurate diagnoses, customised therapies, and improved patient outcomes in the future (Marvao et al., 2020).

6. Applications of AI in Oncology and Pathology

Machine learning (ML) has shown enormous potential in the disciplines of cancer and pathology. ML algorithms have proven their capacity to interpret a wide variety of medical imaging modalities, including histopathology slides, radiological scans, and endoscopic pictures, with excellent accuracy. These capabilities allow the detection and categorisation of distinct tumor forms, considerably enhancing diagnostic precision and treatment planning (Zhang et al., 2023). Since the first FDA clearance of an AI-enhanced medical device in 1995, the integration of artificial intelligence into healthcare has progressed substantially. Currently, more than 950 AI and ML algorithms have achieved regulatory clearance, with a particular emphasis on radiology and cancer applications (FDA, 2024). These results emphasise the increasing relevance of AI in providing better, quicker, and more tailored treatment for cancer patients. Table 4 provides an overview of the FDA-approved AI-based radiological software systems utilised in clinical cancer applications (FDA, 2024).

Table 4 Overview of FDA-approved AI-based radiological software systems used in clinical oncology applications.

Device	Point of interest	Device	Company
Breast cancer	Finding suspected breast cancer lesions	Bu-cad	Taihao Medical Inc.
		Koios DS	Koios medical, inc.
		Mammoscreen 2.0	Therapixel
		Lunit INSIGHT MMG	Lunit inc.
		Saige-Q	Deephealth, Inc.
	The categorisation of breast density by BI-RADS	Visage breast density	Visage Imaging gmbh
		Imagio breast imaging system	Seno medical instruments, inc.
		Powerlook Density Assessment Software V4.0	Icad inc.
		Volpara imaging software	Volpara health technologies limited
	Detection of possible breast abnormalities	Mammoscreen	Therapixel
		Healthmammo	Zebra medical vision ltd.
		Genius ai detection	Hologic, inc.
		Transparatm	Screenpoint medical b.v.
		Profound AI Software V2.1	Icad inc.
		Cmtriage	Curemetrix, Inc.
		Transparatm	Screenpoint medical b.v.
		Koios DS for Breast	Koios medical, inc
		Powerlook Tomo Detection V2 Software	Icad inc.
	The mammography-based BI-RADS breast density categorisation	Wrdensity by Whiterabbit.ai	Whiterabbit.ai Inc.
		Densitas densityai	Densitas, inc.
		Profound™ AI Software V2.1	Icad, Inc
		Dm-density	Densitas, inc.
		Volpara imaging software	Volpara health technologies limited
		Denseemammo	Statlife
Prostate cancer	MRI image-based carcinoma of the prostate diagnosis and screening	Prostatid	Scanmed, LLC
	Finding and evaluating worrisome areas on PSMA PET/CT quantitatively	Apromise	Exini diagnostics ab
	Prostate Illness and cancer detection program	QUIBIM Precision Prostate (qp-Prostate)	Quibim s.l.
	The mpmri-based PI-RADS prostate density categorisation	Proview	Ge medical systems scs
		A view lcs	Coreline soft co., ltd.
		Quantib prostate	Quantib BV
		Clearread CT	Riverain technologies, llc
Lung cancer	Analysing CT images to identify solid-subsolid nodules	Syngo.CT Lung CAD (Version VD20)	Siemens Healthcare gmbh
	Identify suspected pulmonary nodules	Optellum virtual nodule clinic, optellum software, optellum platform	Optellum ltd
		Auto lung nodule detection	Samsung electronics co., ltd.
		Inferread Lung CT.AI	Beijing infervision technology co., ltd.
		Aview lcs	Coreline soft co., ltd
		Syngo.ct lung cad	Siemens medical solutions, inc
	Imaging for lung and liver cancer diagnosis	Arterys MICA	Arterys inc
Brain	Interpreting brain MRI scans	Neuroquant	Cortechs Labs, Inc

	Finding and classifying the many parts of the brain	Quantib brain 1.2 CT copilot Cneuro cmri	Quantib BV Zepmed Combinostics oy
Miscellaneous	PET scan data processing, measurement, and reporting	Apromise X	Exini diagnostics ab
	Identification of questionable lesions for thyroid and breast cancer	Koios DS	Koios medical, inc.
	Software for radiography of cancer-suspicious lesions	Saige-dx	Deephealth, Inc.
	A PET/CT system that creates pictures with attenuation correction	Discovery mi gen2	Ge medical systems, llc.
	Software for detecting cancerous lesions in MR images	Ezra plexo software	Ezra ai inc.
	Software for radiological imaging of cancerous tumours	Quantx	Quantitative insights, inc.
	Reconstruction of CT images	Deep learning image reconstruction	Ge medical systems, llc.
	An algorithm for reducing noise	Subtlepet	Subtle medical, inc.
	Make ROI outlines for dosimetry and quantitative/statistical evaluation.	Quantitative Total Extensible Imaging	Aiq solutions, inc.
	Help with the examination of a questionable lesion on an MRI or CT scan	Arterys oncology dl	Arterys inc.
	CT and MRI analysis for dosimetric reasons	Radiomics app	Microsoft corp.
	CT algorithm for noise reduction	Pixelshine	Algomedica

6.1. Combining pathology and oncology with machine learning

The integration of machine learning (ML) with pathological and radiological data has shown considerable promise for improving cancer diagnosis and therapy. By merging these complimentary domains, ML algorithms may increase the accuracy, efficiency, and customisation of cancer diagnosis and treatment. These developments might lead to earlier diagnosis, more precisely tailored therapy, and improved patient outcomes (Cuocolo et al., 2020). AI-powered diagnostic systems in oncology, especially those employing deep learning, may interpret digital pathology images such as histopathology slides. These technologies help pathologists in crucial activities, including tumor identification, subtyping, grading, and discovering biomarkers that are critical for choosing the proper course of therapy. This AI-driven method has promise in speeding procedures, decreasing diagnostic mistakes, and providing more customised therapy alternatives. Table 5 provides an overview of the ML algorithms used for grading, lesion identification and characterisation and risk assessment.

Table 5 Overview of ML algorithms applied to grading, lesion detection and characterisation and risk assessment.

Ai used for	Aim	Interpretation	reference	ML algorithm
Risk assessment	To evaluate ML-based approaches for risk assessment in comparison to two well-known clinical techniques (BCRAT and BOADICEA)	Auc adaptive boosting= 0.88 Auc random forest= 0.62 (brcat) Predictive accuracy of adaptive boosting = 0.90 predictive accuracy of markov chain monte carlo= 0.59 (boadicea)	(Ming et al., 2019)	Monte Carlo Markov Chain -Generalised linear mixed model -Quadratic analysis of discriminants -Adaptive boosting

	To create a breast cancer risk model based on automated mammography	AUC was 0.70.	(Yala et al., 2019)	-K-nearest neighbours in a random forest -Model of regression - Deep learning
	To calculate prostate cancer risk	The training and validation sets have respective aucs of 0.73 and 0.89.	(Roffman et al., 2018)	Neural network
	To assess the risk of lung cancer	Both the training and validation sets have sensitivity values of 0.80 and 0.81, and specificities of 0.80 and 0.75, respectively.	(Hart et al., 2018)	Neural network
	To assess the risk of pancreatic cancer	While the AUC for the training and testing sets is 0.86 and 0.85, respectively, the sensitivity (training set) and specificity (testing set) are 0.87 and 0.81.	(Muhammad et al., 2019)	Artificial neural network
Identification and description of lesions	DBT-based automatic identification of breast cancer	AUC was 0.84.	(Rodriguez-Ruiz et al., 2019)	Convolutional neural network
	Automated detection and classification of mammography lesions	AUC was 0.85.	(Ribli et al., 2018)	Convolutional neural network
	Mammography tests that automatically detect breast cancer	0.99 was the negative predictive value.	(McKinney et al., 2020)	Deep learning
	Breast tumours classified as benign or malignant automatically using DCE MRI	AUC was 0.81	(Herent et al., 2019)	Deep learning
	Automatic detection and description of prostate lesions using MRI	AUC was 0.88	(Bonekamp et al., 2018)	Random forest
	Automatic liver lesion classification using MRI	Specificity was 0.98, Sensitivity was 0.92, and Accuracy was 0.92	(Hamm et al., 2019)	Convolutional neural network
	Adrenal adenomas are automatically identified from MRI	Accuracy of 0.80	(Romeo et al., 2018)	Texture analysis
	Self-detecting polyps from clinical colonoscopies	Sensitivity was 0.94 and Specificity was 0.96	(P. Wang et al., 2018)	Convolutional neural network
	Automated identification of pertinent image areas and evaluation of cytopathology image malignancy scores Performance on par with that of a skilled cytopathologist	Performance on par with those of skilled cytopathologists	(Dov et al., 2020)	Deep learning

	Automatic categorisation of colposcopy images	Accuracy was 50%	(Sato et al., 2018)	Deep learning
Grading	To classify gliomas as either high- or low-grade	Accuracy was 0.94	(X. Zhang et al., 2017)	Support vector machine
	To forecast the methylation state of the MGMT promoter in glioblastoma	The accuracy was 0.87.	(Levner et al., 2009)	Neural network
	To forecast MGMT promoter methylation status, 1p/19q codeletion, and IDH1 mutations in gliomas	IDH1 mutations had an accuracy value of 0.94, 1p/19q codeletion had a value of 0.92, and MGMT promoter methylation status had a value of 0.83.	(P. Chang et al., 2018)	Convolutional neural network
	To differentiate between Luminal A and Luminal B breast cancers	Both the total variance and sum entropy aucs were 0.83.	(Holli-Helenius et al., 2017)	Texture analysis
	Image analysis of breast tumour tissue stained with haematoxylin and eosin to determine the molecular marker status	Accuracy was between 0.75 and 0.94	(Couture et al., 2018)	Convolutional neural network
	Grade automatically using Gleason	The agreement between the pathologist and the model is 0.71 and 0.75, respectively.	(Arvaniti et al., 2018)	Deep learning
	Grade automatically using Gleason	The accuracy was 0.70.	(Nagpal et al., 2019)	Deep learning
	Differentiating between high-grade and low-grade renal carcinomas with clear cell	The training and validation sets have respective aucs of 0.88 and 0.91.	(X. Sun et al., 2019)	Support vector machine
	To forecast the NSCLC pathologic stage	AUC was between 0.70 and 1	(Yu et al., 2010)	Random forest
	To predict the histologic lung cancer subtypes	The corresponding aucs for K-nearest neighbours, Random Forest, and Naive Bayesian are 0.69, 0.72, and 0.64.	(W. Wu et al., 2016)	-Random forest -naive bayesian -k-nearest neighbors

* BCRAT (Breast Cancer Risk Assessment Tool), BOADICEA (Breast and Ovarian Analysis of Disease Incidence and Carrier Estimation Algorithm), AUC (Area under the Receiver Operating Characteristic curve), DBT (Digital Breast Tomosynthesis), DCE MRI (Dynamic contrast-enhanced magnetic resonance imaging) AUC (Area under the Receiver Operating Characteristic curve), IDH1 (Isocitrate dehydrogenase 1), MGMT (O-6-Methylguanine-DNA Methyltransferase), AUC (Area under the Receiver Operating Characteristic curve) NSCLC (Non-small cell lung cancer).

Machine learning (ML) offers several prospective benefits in cancer therapy, from early screening to monitoring and customising patient care. However, there are still problems that need to be overcome before it can be employed entirely in the clinic. One crucial issue is overfitting, which occurs when ML models concentrate too much on training data, making it impossible for them to operate effectively with fresh data. This may be caused by low-quality data, inadequate data processing, or excessively sophisticated models (Bradshaw et al., 2023; Challen et al., 2019). As a consequence, these models perform well during training but fail when employed in real-life instances. To prevent this, we may employ approaches such as data augmentation, regularisation, and cross-validation to assist models in remaining flexible and more accurate.

Another problem is the interpretability of ML models. Many of these models, intense learning models, might be challenging to grasp. They function as "black boxes," and clinicians may not know why the model has reached an inevitable conclusion (Adamson & Welch, 2019). This lack of transparency might make it difficult for physicians to trust the system. To solve this problem, researchers are creating explainable AI (XAI), which produces models that describe why they make particular decisions. For example, saliency maps might show the essential aspects of a medical picture that help the model reach its conclusion. This makes it simpler for clinicians to follow and accept the model's logic. The quality of the training data is also a considerable problem. If the data utilised to train ML models are biased or erroneous, the model could yield misleading conclusions. In domains such as pathology and radiology, professionals can differ in their ability to make a diagnosis. This may pose difficulties with the data used for training (Cuocolo et al., 2020).

A unique deep learning-based risk assessment model was created that incorporated full-field mammography and traditional risk variables (Kim et al., 2023; Arasu et al., 2023). Compared with the Tyrer–Cuzick model, this hybrid technique shows superior performance, demonstrating a greater area under the receiver operating characteristic curve, especially among high-risk groups such as African American women (Boughey et al., 2010). The model's prediction accuracy remained stable even when conventional risk factor data were absent, indicating that the model is a feasible choice for patients lacking thorough family history information. By using imaging patterns beyond the traditional density of breast estimates, the deep learning model generated more sophisticated risk evaluations, which might boost individualised preventative tactics.

While the deep learning-based technique exhibited promising results, it has drawbacks that deserve additional research. The model's performance gains over the Tyrer–Cuzick model, especially among high-risk subgroups such as African American women, may not be generalizable across other patient populations (Ozcan et al., 2023). Additionally, the dependence on full-field mammography might exclude those without access to such imaging technologies, thus aggravating healthcare inequities. Moreover, the model's capacity to generate more detailed risk assessments may not always translate to substantial advances in tailored preventive efforts since the clinical efficacy of these assessments has to be demonstrated (Howard et al., 2023; Qi et al., 2022). Therefore, more studies are needed to overcome these possible limitations and ensure the robust and fair deployment of our deep learning model in breast cancer risk assessment.

6.2. Artificial intelligence and digital biomarkers in precision pathology

The discovery of improved immunotherapies has dramatically revolutionised how cancer is treated, from being regarded as a last resort to being a first-line treatment. To ensure that patients receive optimal therapy, it is crucial to research the various kinds of cells inside tumours and how the immune system responds to them. This allows clinicians to identify the correct immune-modulating medicines, which may strengthen the patient’s immune system and target cancer more accurately (Bødker et al., 2020). Tumours, including their spread (metastasis), are exceedingly adaptive. They may resist being noticed by the immune system and continuously evolve due to diverse variables both within and outside the body. Immune-modulating drugs are increasingly recognised as crucial advances in cancer therapy (Sundaram et al., 2018).

Studies have demonstrated that for immuno-oncology therapies to operate their best, it is necessary to understand how cancer cells and immune cells interact in the tumor environment (Qi et al., 2021; Guo et al., 2023). Artificial intelligence (AI) helps map these interactions, making it easier to develop and test digital tools that can predict how well treatments will work (An AI-based Digital Score of the Tumor-Immune Microenvironment Predicts Benefit to Maintenance Immunotherapy in Advanced Esophagogastric Adenocarcinoma, 2024). AI-supported methods aid in identifying proper therapies by assessing cancer tissue pictures and other standardised data (Koh et al., 2021). Precision pathology incorporates not only these AI and digital technologies but also the trustworthy techniques utilised in regular lab work. Mathematical models also aid in determining choices for therapy, establishing the foundation of what is known as "precision oncology" (Huss et al., 2023). AI is also the foundation for digital biomarkers, which include more digital and quantifiable data from various sources to affect clinical practice, notably in the choice of immunological treatment. Table 6 illustrates instances of decision-making that help with the use of AI in precision oncology and precision pathology.

Table 6 Examples of decision assistance using AI in precision oncology and precision pathology.

	AI-assisted support	Digital Biomarker
Precision pathology	Metastases detection	Disease diagnosis
	Multiplex immunohistochemistry	(Tumor) Immune infiltrates
	Whole sllide imaging	Prognostic biomarker
	Image analysis	
	PD-L1 quantification	
Precision oncology	Large date extraction	Personalised medicine and response prediction
	Multidimensional data analysis	Cell- and Gene therapy
	Mutation detection and analysis	IO/non-OI combination therapies
	Spatial transcriptomics	Immune escape prediction
	Drug development	Metastases assessment

Source: Lin et al., 2022.

Modern AI tools are changing precision oncology. For example, AI is used to detect cancer-causing genes, research genetic alterations, and design tailored therapies as alternatives to standard chemotherapy. It is also vital to follow patients' health throughout treatment, such as by utilising electrocardiograms to identify specific gene variations (Mao et al., 2024; Xie et al., 2023). AI techniques such as single-cell genomics and cancer gene panels assist in monitoring illness and suggest therapy

(Volchkov et al., 2023). One AI system has been designed to handle data for colorectal cancer patients, helping improve their results (Santini et al., 2023). AI also plays a role in telemedicine, enabling real-time monitoring and supporting individualised treatment choices. These improvements highlight how AI is making cancer care more precise, boosting diagnosis, therapy, and quality of life for patients (Lin et al., 2022).

7. AI in Hypertension Control

Hypertension is recognised as the leading cause of cardiovascular disorders worldwide. The number of persons increased from 594 million in 1975 to 1.13 billion by 2015, notably in countries with low and moderate incomes. This rise is attributed to various causes, including aging, lifestyle changes, and population expansion (Zhou et al., 2016). The American College of Cardiology and the American Heart Association have decreased the threshold for diagnosing stage 1 hypertension from 140/90 mm Hg to 130/80 mm Hg. Because of this, more individuals are now deemed to have hypertension (Whelton et al., 2017). Hypertension is challenging to treat since numerous factors, such as heredity, the environment, and lifestyle, may cause it. Even though blood pressure regulation is straightforward, only 14% of individuals worldwide have a systolic blood pressure of less than 140 mm Hg (Egan et al., 2019).

New artificial intelligence (AI) approaches, including machine learning, may assist in forecasting hypertension by integrating cardiac risk factors with data on genetics, behaviour, and the environment. AI can also help identify it via basic data such as age and lab tests (Chaikijurajai et al., 2020; Kohjitani et al., 2024). AI-based devices are also being researched to measure blood pressure all the time, which may enhance the identification of conditions such as masked hypertension (Elgendi et al., 2019; Chaikijurajai et al., 2020). The key advantage of employing AI in treating hypertension is its capacity to forecast cardiac issues, rate patients by risk, and determine what keeps specific individuals from regulating their blood pressure correctly (Pei et al., 2018). AI models may predict hypertension by assessing numerous elements, such as genetic and behavioural characteristics, coupled with laboratory testing. In therapy, AI may assist in establishing better blood pressure objectives and uncovering variables that impact cardiac outcomes (Krittanawong et al., 2019). For example, AI studies from trials such as SPRINT and ACCORD-BP have revealed additional variables that affect blood pressure management (Cushman et al., 2010; A Randomised Trial of Intensive vs Standard Blood-Pressure Management, 2017; Laffin & Bakris, 2018) (Bakris et al., 2019). Future AI research in hypertension intends to link big data with genetics, behaviour, and environmental variables to provide individualised therapy. AI might also be utilised in health coaching to assist individuals in becoming more conscious, monitoring their progress, and adhering to their therapy (Chaikijurajai et al., 2020). Table 7 shows the prospective applications of AI in the treatment and prevention of high blood pressure.

Table 7 Possible uses of AI in the treatment and prevention of high blood pressure.

Reference	Aim	Method
(Golino et al., 2014; Kanegae et al., 2020; X. Li et al., 2017; Y.-H. Li et al., 2017; Maxwell et al., 2017; Pei et al., 2018b; Sakr et al., 2018; Ye et al., 2018)	Recognising the signs of hypertension	Utilise information from genetics, behavior, socioeconomics, environment, and treadmill stress tests to forecast the likelihood of getting hypertension. Find novel genes linked to hypertension.
(Samant & Rao, 2013)	Making a diagnosis of hypertension	Using vital signs, demographic information, conventional CV risk factors, and routine laboratory testing in large patient groups to accurately diagnose hypertension.
(Khalid et al., 2018; R. Liang et al., 2014; Y. Liang et al., 2018; Miao et al., 2017; Monte-Moreno, 2011; Slapničar et al., 2019)	Blood pressure measurement	Use ML and DL algorithms to analyse the pulse oximeter's PPG signal in order to estimate blood pressure. Calculate blood pressure using a smartphone's PPG signal.
(Poplin et al., 2018)	Blood pressure prediction	Estimate blood pressure using demographic information, lifestyle factors (such as alcohol, tobacco, and physical activity), and retinal fundus photos.
(Guthrie et al., 2019; Y. Li et al., 2019; R. Mohammadi et al., 2019; J. Sun et al., 2013)	Identifying and anticipating obstacles to blood pressure management	Calculate the chance of developing uncontrolled hypertension. Determine the elements that affect treatment effectiveness and adherence.

(Alaa et al., 2019a, 2019b; W. Chang et al., 2019; *Srivastava: A Note on Hypertension Classification... - Google Scholar*, n.d.; X. Wu et al., 2020)	Estimating the risk of cardiovascular disease in hypertension	Assign patients to risk groups and forecast CV outcomes in HTN patients.
(Israel & Grossman, 2017; Lacson et al., 2019)	Changing the blood pressure goals	Discover the variables linked to adverse events, CV outcomes, and important rcts that advise various BP objectives.

* AI (artificial intelligence), BP (blood pressure), CV (cardiovascular), DL (deep learning), HTN (hypertension), ML (machine learning), PPG (photoplethysmography), RCTs (randomised controlled trials).

8. AI in Diabetes Control

The number of people with diabetes has increased worldwide, especially in nations such as China. In 1980, only 0.67% of people in China had diabetes, but by 2017, this figure had increased to 11.2% (Cai et al., 2021). There are considerable problems in treating diabetes, such as recognising it early, preventing it, and controlling it. These issues are exacerbated by unequal healthcare resources and the need for individuals to monitor their status and adjust their lives. To address these challenges, specialists are looking at artificial intelligence (AI) technologies for controlling diabetes (Hermanns et al., 2022; ElSayed et al., 2022). AI employs machine learning to anticipate when someone could acquire diabetes, screen for the condition, and regulate risk factors. For example, methods such as logistic regression and gradient-boosting decision trees have demonstrated great accuracy, with rates as high as 94.9% (Guan et al., 2023). AI is also helping improve diabetes screening, with models such as support vector machines and deep learning having outstanding success in distinguishing diabetes from basic, noninvasive testing (LeCun et al., 2015). AI-powered systems are currently being designed to assist clinicians in making better judgments, monitoring patients remotely, and recommending individualised therapies (Mackenzie et al., 2023). Table 8 shows the AI used to test for and anticipate diabetic complications. AI plays a crucial role in controlling diabetes in various ways. It assists with patient education, nutrition recommendations, physical treatment ideas, and blood sugar level testing. New AI technologies, such as smartphone applications for monitoring meals and AI-powered insulin calculators, help patients take better care of themselves. For example, the GoCARB system is as accurate as dietitians in determining how much carbohydrates a person consumes (Vasiloglou et al., 2018). Additionally, AI models have been built to increase insulin dosages and anticipate blood sugar levels. They are excellent at forecasting low and high blood sugar levels (Chen et al., 2022). These advances highlight how AI can enhance diabetes treatment, from preventing it early to controlling it better for each individual, which may lead to excellent health for people.

Table 8 Uses of AI to screen for and forecast diabetes complications.

Aim	Interpretation	ML method	Reference
To use risk indicators to forecast the emergence of problems associated with diabetes.	The models also showed good performance on the external T2D cohorts, with a C index between 0.66 and 0.833. The only models with results that were almost useless were the neuropathy and retinopathy models.	ANN	(Lagani et al., 2015)
To use risk indicators to forecast the emergence of problems associated with diabetes.	The accuracy of the final models was up to 0.838.	RF, SVM, and LR	(Dagliati et al., 2018)
To use risk variables to evaluate the likelihood of problems.	Assessing amputation risk is 90% accurate, determining the kind of risk (development or progression) and stroke risk is 100% correct, and determining global and infarct risk is 72.45% accurate.	case-based reasoning	(Armengol et al., 2001)
To use risk variables to calculate the chance of amputation in individuals receiving canagliflozin.	With a C value of 0.81, LASSO produced the best prediction.	LASSO regression	(L. Yang et al., 2021)
To evaluate how issues start and progress over time using risk factors (T1D).	Less than 10% of the population was predicted in the erroneous state on both DDO-DBN and EI-DBN.	BN	(Marini, Trifoglio, Barbarini, Sambo, Di Camillo, et al., 2015)
To use longitudinal data on hospitalisation to forecast the occurrence of ten specific problems (T2D).	In contrast to prior models, which had an accuracy range of 66% to 76%, the prediction accuracy for myocardial infarction varied from 73% to 83%.	RNN	(Ljubic, Hai, Stanojevic, et al., 2020)

To use longitudinal data to measure how comorbidities evolve.	Offered a network theory-based study paradigm to comprehend the course of chronic diseases and the comorbidities that develop over time.	Network analysis	(Khan et al., 2018)
To calculate the chance of acquiring DR within two years using retinal scans and risk factors.	The three-field DL technique generated an AUC of 0.79 in the internal validation set	CNN	(Bora et al., 2021)
To predict the start of chronic kidney disease (CKD) using retinal images and risk factors.	The C index for the external test set was 0.719, whereas the C index for the internal test set was 0.845.	CNN	(K. Zhang et al., 2021)
To predict, at the patient level, the likelihood of severe diabetic retinopathy (DR) worsening over a two-year period using retinal images.	AUC is 0.79.	CNN	(Arcadu, Benmansour, Maunz, Willis, Haskova, et al., 2019)
To demonstrate AI algorithms for DR screening using retinal scans.	Aucs for the categorisation of DR as mild, moderate, severe, and proliferative are 0.943, 0.955, 0.960, and 0.972, respectively	DeepDR	(Dai et al., 2021)
	More than mild nonproliferative DR, detecting referral-warranted DR with 91.3% sensitivity and 91.1% specificity.	EyeArt	(Bhaskaranand et al., 2019)
	Aucs were 0.990 for Messidor-2 and 0.991 for eyepacs-1	CNN	(Gulshan et al., 2016)
	Above 85% accuracy, 82% sensitivity, and 86% specificity on average.	morphological image processing and SVM	(Acharya et al., 2009)
	DR was detected with a 77.32% accuracy rate, a 76.89% sensitivity, and a 77.43% specificity.	Fuzzy RF	(Saleh et al., 2018)
Introducing AI systems for metabolic marker-based CKD screening	The best collection of predictors was found to include two metabolites and five clinical factors; their predictive efficacy produced a mean AUC of 0.857.	ML classifiers	(J. Huang et al., 2020)
To demonstrate AI algorithms that use retinal pictures for CKD screening.	AUC between 0.85 to 0.93. AUC of 0.889 with just fundus photos.	CNN CNN	(K. Zhang et al., 2021) (Sabanayagam et al., 2020)
To demonstrate AI systems that use clinical and genetic data to screen for diabetic nephropathy (DN).	85.27%, 83.32, and 85.24% for accuracy, specificity, and sensitivity, respectively.	DT, RF, SVM, BN	(G.-M. Huang et al., 2015)
To use thermogram pictures to categorise thermograms according to the degree of diabetic foot problems.	Accordingly, the F1 score, specificity, accuracy, precision, and sensitivity were 97.2%, 95.08%, 95.09%, and 95.08%, respectively.	CNN, k-means clustering technique	(Khandakar et al., 2022)
To use smartphone photos to calculate the chance that diabetic foot sores will heal.	F1 score of 0.873, recall of 0.923, accuracy of 0.811, precision of 0.828, and AUC of 0.734.	ANN, RE and SVM	(R. B. Kim et al., 2020)
To use corneal confocal microscopy pictures to detect diabetic peripheral neuropathy	The system's sensitivity, specificity, and AUC were 67.7%, 86.7%, and 0.83, respectively.	CNN	(Williams et al., 2020)
To use clinical data to predict and distinguish between nondiabetic renal disease and diabetic kidney disease.	The RF and SVM approaches have respective aucs of 0.953 and 0.947.	RF, SVM	(W. Zhang et al., 2022)

To use corneal confocal microscopy pictures to detect diabetic peripheral neuropathy	AUC is 0.95, sensitivity is 92%, and specificity is 80%.	CNN	(Salahouddin et al., 2021)

*AI (artificial intelligence), ANN (artificial neural network), BN (Bayesian network), RF (random forest), SVM (support vector machine), RNN (recurrent neural network), CNN (convolutional neural network), ML (machine learning), LASSO (least absolute shrinkage and selection operator), DT (decision tree), NB (naive Bayes), DBN (dynamic Bayesian networks), DDO-DBN (data-driven only network), EI-DBN (network designed with expert intervention), AUC (area under the curve), EHR (electronic health record), DN (diabetic nephropathy), DR (diabetic retinopathy), T1D (type 1 diabetes), T2D (type 2 diabetes), C index (concordance index).

Previous research has indicated that AI approaches may assist in predicting and diagnosing the consequences of diabetes, such as diabetic retinopathy, renal disease, and foot difficulties (Dai et al., 2024; Marini et al., 2015; Ljubic et al., 2020). AI algorithms that employ retinal scans and medical data have demonstrated significant accuracy in recognising individuals who are at high risk of these disorders (Arcadu et al., 2019; Abràmoff et al., 2016). Moreover, AI presents various opportunities to construct individualised, data-based therapies for diabetes (Carspecken et al., 2013; Ash, 2003). However, several hurdles still exist in the complete use of AI in diabetes management. These include issues regarding data quality, patient privacy, lack of acceptance of AI technologies, and difficulties in successfully introducing AI into medical practice (Ash, 2003).

9. Artificial Intelligence in Medical Imaging

Artificial intelligence (AI) is becoming a significant tool in medical imaging, especially in cancer therapy. Deep learning approaches, such as convolutional neural networks (CNNs), are increasingly extensively used to interpret radiological images because they can automatically detect key information in these images (Hosny et al., 2018). This skill is especially beneficial in radiology, where many picture data have to be examined appropriately. CNNs are frequently used for categorising medical pictures, enabling clinicians to discover illnesses, discern the difference between safe and hazardous lesions, and forecast how a patient would fare on the basis of image attributes (Mazurowski et al., 2018). Since there are not always enough massive medical datasets accessible, several strategies, including transfer learning, leveraging off-the-shelf features, and fine-tuning pretrained networks, have been beneficial in overcoming this issue (Hardy & Harvey, 2019). Image segmentation is another crucial task in radiology. This entails distinguishing distinct things in a picture, such as organs, lesions, or other anomalies (Hardy & Harvey, 2019). Convolutional networks have enhanced the success of this task. They operate better than prior approaches that just look at tiny sections of the picture at once. They have been helpful in diagnosing conditions such as brain tumours, prostate glands, and lesions from multiple sclerosis (Yordanova, 2024). In medical imaging, detection implies the discovery of aberrant areas, regions of interest, or bodily structures. In addition to models such as Faster Region-based CNNs, CNNs are employed for applications such as diagnosing breast cancer or recognising intervertebral discs (Shi et al., 2020). Other applications of deep learning in radiology include picture registration, image augmentation, superresolution, and content-based image retrieval. Techniques such as generative adversarial networks are being used to increase the resolution of pictures or recreate low-quality MR images (Comaniciu et al., 2016; Klauschen et al., 2023). These AI systems might improve the accuracy and speed of several imaging-based medical activities. As demonstrated in Figure 3, AI may improve oncology imaging in many ways, from identifying cancer early to monitoring therapy progress, which can lead to improved outcomes for patients. Figure 3 highlights the present and anticipated future uses of artificial intelligence in radiology.

AI algorithms have the potential to increase the accuracy and speed of imaging-based jobs, but they do not always perform better than human specialists do. For example, in lung cancer screening, AI can locate pulmonary nodules and indicate whether they are benign or malignant. However, it can also make errors, such as labelling something as cancer when it is not or missing specific abnormalities that a trained radiologist would see (Giles, n.d.). AI may also assist in identifying incidental lesions in abdominal and pelvic images and discovering and categorising colonic polyps during a colonoscopy in real time, although these systems are not flawless (Gorris et al., 2020; Breugel et al., 2023; Zulqarnain et al., 2023). One challenge with AI models is their ability to function successfully across various groups of individuals. They can perform well on some datasets but struggle with more varied patient groups or unexpected picture patterns. In breast cancer screening, for example, AI may assist in identifying microcalcifications, but it may not always match the thorough interpretation that a radiologist can offer (Ibrahim et al., 2020; Cuocolo et al., 2020).

10. Towards Personalised Theragnostics With AI

The application of artificial intelligence (AI) in theragnostic systems, which attempt to develop individualised treatment regimens and monitor patient reactions in real time, holds significant promise for improvement. Theragnostic system integrates therapy with diagnosis, delivering a more individualised, data-based approach to healthcare. It enables clinicians to select particular therapies and track how patients react throughout their care (Bilgin et al., 2024). AI may make theragnostic therapies more precise, efficient, and personalised to each patient, particularly in treating diverse illnesses (Khan, 2023). By employing powerful machine learning, AI can assess diverse types of clinical data, such as genetics, pictures, and real-time health monitoring, to recommend individualised therapies and forecast how well they work (Lu et al., 2024). AI techniques may also assist physicians in adjusting treatment strategies as patients' needs and reactions vary. Although AI has potential in the field of theragnostics, it is still being extensively studied. This creates prospects for additional research and development to enhance patient-focused treatment (Wojtara et al., 2023; Moulik et al., 2020). Although AI has the potential to improve prognostic systems by increasing treatment regimens and patient monitoring, certain obstacles remain (Bilgin et al., 2024). While the promise of AI to make therapies more accurate and efficient is intriguing, there are concerns regarding how effectively it can be used and trusted (Labkoff et al., 2024). The successful use of AI in complicated medical choices requires extensive testing to ensure that it can handle various patient circumstances. Additionally, it may be challenging to collect the high-quality clinical data required for AI, such as genetics and health monitoring data, which might delay its usage in theragnostics (Davenport & Glaser, 2022). Additionally, some physicians may be apprehensive about depending too much on AI and may prefer to rely on their expertise to alter therapies for their patients (Golden et al., 2024). Even though AI has excellent prospects in the field of genetics, additional studies are still needed to overcome these difficulties and ensure that it can actually enhance individualised treatment (Johnson et al., 2020).

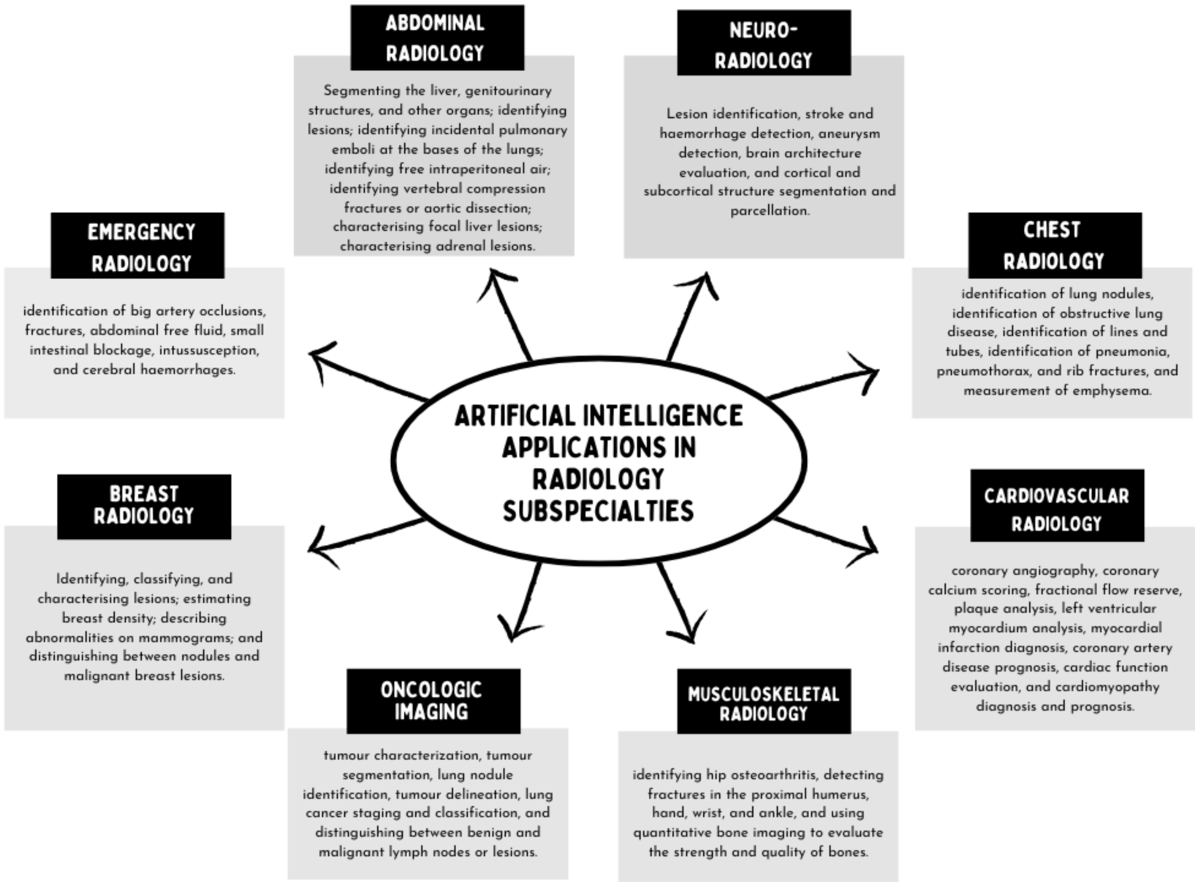

Figure 3 illustrates the current and possible future applications of artificial intelligence in radiology. *Source:* (Bitencourt et al., 2021; Cellina et al., 2022; Duong et al., 2020; Jiang et al., 2020; Mervak et al., 2023; Muscogiuri et al., 2022; Novosad et al., 2020; Olczak et al., 2017; Paudyal et al., 2023; Sadaghiani et al., 2021; Schalekamp et al., 2022; Sunoqrot et al., 2022; Ta et al., 2018; K. Wang et al., 2019; Yordanova, 2024a).

11. Limitations and Problems of AI-driven Theragnostic Methods

There are various key issues and concerns when applying artificial intelligence in healthcare. These include preserving data security and privacy, correcting biases in the algorithms, ensuring that relevant rules are in place, and obtaining patient acceptance of this new technology.

11.1. Data security and privacy

Using AI systems in healthcare creates vast volumes of sensitive medical and personal data. This raises significant issues regarding data security, namely, the potential for illegal access and abuse. This paper underlines the need for robust data encryption, effective access restrictions, and adherence to legislation such as the Health Insurance Portability and Accountability Act to guarantee that patient privacy is safeguarded (Li et al., 2024).

11.2. Algorithmic biases and their potential for discrimination

Artificial intelligence algorithms may display biases resulting from the training data employed in their creation, possibly leading to discrepancies in their performance and clinical results. For example, skin cancer diagnosis models may display greater accuracy for individuals with lighter skin complexions, which is attributable to the underrepresentation of darker skin tones in the training datasets. Similarly, gender biases have been discovered in medical imaging datasets. To address these problems, this paper advises the use of varied and representative datasets to limit the spread of such biases inside AI systems (Yang et al., 2024; Mittal et al., 2024).

11.3. Resistance to AI adoption and regulatory challenges

Established healthcare systems generally display a cautious and conservative stance, which might hamper the adoption of AI-driven technology (Shamszare & Choudhury, 2023; Sivaraman et al., 2023). Clinicians and administrators may be hesitant to embrace AI-based solutions owing to worries about interrupting their traditional processes and reservations over the apparent advantages of this developing technology. Additionally, the technological complexity needed to smoothly integrate AI systems with current health information systems and electronic health records might present substantial barriers to their deployment.

11.4. Training and expertise

Providing rigorous and continuing training programs for medical personnel is vital for successfully employing AI technology in healthcare; without sufficient education and knowledge of these new technologies, their uptake and usage might be hindered, diminishing the advantages for both physicians and patients. It is crucial to build effective training programs that provide healthcare staff with the information, skills, and confidence they need to employ AI-driven technologies in their regular activities successfully. This will allow them to fully use these technologies to enhance patient care and outcomes (Varnosfaderani & Forouzanfar, 2024; Alowais et al., 2023).

11.5. Regulatory frameworks

Regulatory bodies, such as the U.S. Food and Drug Administration (FDA), the UK Medicines and Healthcare Products Regulatory Agency, and other worldwide authorities, are vital in licensing AI-based medical technology. This paper underscores the need for a solid regulatory mechanism to ensure that AI technologies in healthcare are safe and dependable. It lists the FDA’s framework for Software as a Medical Device and the European Union's General Data Protection Regulation as significant standards for how AI is utilised in healthcare (Bengio et al., 2024; Tang et al., 2023; Peters & Visser, 2023).

11.6. Patient acceptance of AI

Gaining patient approval is key for effectively incorporating AI into healthcare. Patients' trust, comprehension, and attitudes toward the dangers and advantages of these technologies strongly determine their willingness to accept them. The article cites examples such as the Mayo Clinic's AI-powered chatbot and the National Health Service's virtual nursing assistant, which prove that people may accept AI. However, it also underlines the necessity for clear communication to address patient concerns by discussing both the benefits and limits of AI technologies (Clark & Bailey, 2024; Bhattacharya, 2023; Altamimi et al., 2023; Camaradou & Hogg, 2023).

12. Conclusion

In precision medicine, AI-integrated theragnostic systems can have a significant impact. These technologies combine accurate diagnosis with personalised therapies for each patient. This research reveals that AI technologies, such as machine learning and digital twin models, are effective in establishing customised treatment regimens and increasing real-time monitoring. By reviewing complicated data, AI can increase diagnostic accuracy and alter therapies for better outcomes. This makes AI a crucial tool for addressing illnesses such as cancer and heart issues. Despite its advantages, several difficulties persist. AI requires high-quality and diversified data to prevent biased outcomes. Additionally, good data security is essential to ensure that patient information is secure. In addition, rigorous restrictions and healthcare practitioners' concerns about interpreting AI conclusions may impede its usage in clinics. Future research should address these difficulties by establishing more apparent AI models, extending datasets, and defining uniform principles for AI in healthcare. Even if there are limitations, incorporating AI in theragnostic systems might lead to more tailored and effective treatment, marking a large step forward in precision medicine.

Ethical Cconsiderations

The authors have ensured that all ethical guidelines for the conduct and reporting of research have been followed. There were no human or animal subjects involved in this review; thus, no ethical approval was needed. Each author contributed significantly to the research and writing of this article, affirming their agreement with its content.

Conflict of Interest

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