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Review Article

# Artificial Intelligence in Oncology: Integrating Screening, Diagnosis, Prognosis and Treatment

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**ABSTRACT**
Cancer is a global health challenge characterized by complex, adaptive biological processes and substantial mortality rates. Early detection and precise treatment personalization of cancer is elusive despite all the advances in oncological screening, diagnosis and treatment. Artificial intelligence (AI) emerges as a transformative technology in oncology by leveraging vast and varied datasets, including clinical records, genomic profiles, imaging, and pathology to augment decision-making and improve patient outcomes. AI encompasses machine learning (ML) and deep learning (DL) techniques capable of identifying intricate patterns in high-dimensional data unavailable to human cognition alone. These techniques are applied across the cancer care continuum, enabling improved risk stratification in screening, early diagnosis through radiological and histopathological image analysis, and enhanced prognostic modelling that surpasses traditional statistical methods. AI-driven models facilitate individualized treatment planning with adaptive radiotherapy, robotic surgery assistance, and optimization of chemotherapy and immunotherapy regimens, improving therapeutic efficacy while minimizing toxicity. This review synthesizes evidence across AI-driven screening, diagnosis, prognosis, treatment optimization and drug discovery, highlighting methodologies, clinical performance and future directions for AI in oncology. Key findings demonstrate that AI achieves expert-level performance in imaging-based cancer screening (mammography, colonoscopy, dermoscopy), surpasses traditional statistical models in multi-cancer prognostic prediction, and enables individualized treatment planning through adaptive radiotherapy, robotic surgical guidance, optimization of chemotherapy and immunotherapy regimes. Emerging applications in generative drug engineering and multi-cancer liquid biopsy detection further highlight AI's expanding translational potential.

## INTRODUCTION

Cancer remains a significant global health burden, contributing substantially to both illness and mortality (1). It is not a single disease, but rather a complicated interaction of the dynamic, self-sustaining and adaptive processes that involve the microenvironment of the host in an intricate way. The global cancer burden keeps on increasing in the past decades, and it can be attributed to aging of the global population, changing lifestyles and unresolved challenges in diagnosis and treatment (2, 3). The United States alone has registered about 1.9 million new cancer cases and 612,000 cancer deaths in 2023, while other parts of the world have also recorded same disturbing trends (4).

The prognosis and survival rates have significant differences based on the type of cancer and the stage at which the cancer is diagnosed. For example, although 5-year survival rates after surgery with resection of early-stage lung cancer are 70-90%, the survival rates among the total population are 19% among women and 13.8% among men. This notable disparity underscores the critical importance of timely detection and accurate staging (5, 6). One particular concern is the fact that very few aggressive cancers like lungs, gastric, pancreatic, esophageal and oral cavity malignancies are diagnosed at an early stage. Only 44.3% of the cancers in England were diagnosed at stage I or II in 2018 and for certain types of cancers the rate of early detection is less than 30% (7-9). The fact that cancer can recur, develop and be resistant to treatment despite advances in screening, surgery and therapy, highlights the pressing necessity

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of more specific and targeted treatment methods. impactful enabling technology that is transforming the practice of oncology.

## Integration of Artificial Intelligence in Oncology

AI refers to computer systems designed to mimic human cognitive processes like learning, reasoning, and problem-solving—through algorithmic execution (10). In oncological research, AI is being used to process large, multifaceted data sets of clinical data, genomic and imaging scans, as well as pathology slides. It aims at augmentation or automation of major cancer care areas such as screening, diagnosis, prognosis, choice of treatment, and prevention (11-13). Machine learning (ML) is a fundamental part of AI; whereby computational models are trained to detect patterns and generate predictions using historical data. There are three categories of ML algorithms: Supervised learning (learns with labelled data e.g., cancer vs. non-cancer), Unsupervised learning (learns unknown patterns in unlabeled data e.g., clustering gene expression profiles) and Reinforcement learning (learns optimal decisions by trial and error feedback loops (14, 15). Deep learning (DL) is one of the strongest applications of AI in ML and involves the use of artificial neural networks (ANNs) organized in layers to learn non-linear relationships that are complex. DL is also good at unstructured data including medical images and free-text clinical notes (16, 17).

DL is impactful in areas that require high-dimensional features extraction, including radiology, histopathology, and genomics. As an example, convolutional neural networks (CNNs) have been demonstrated to play at an expert level in activities such as breast cancer mammogram classification or the detection of lung nodules on CT scans (18-20). One such application of DL is a neural network model that was designed to predict the risk of pancreatic cancer given a set of clinical variables e.g., age, smoking, alcohol consumption, and ethnicity. These models are based on the ANN architecture that includes three layers: Input layer (raw clinical or imaging data), Hidden layer (process features with weighted nodes and activation functions), and the output layer (provides probability-based predictions e.g., malignancy) (21). Models have been democratized by means of DL frameworks such as TensorFlow and PyTorch, and platforms such as Google Collaboratory provide access to GPUs (free, cloud-based) to train models (22, 23). Logistic regression, decision trees, SVM and ensemble methods are examples of traditional ML algorithms that have long been applied in cancer risk modelling, prediction of treatment response and stratification of patients (24-28). ML is more accurate prognosis modelling tool in predicting both survival and recurrence risk, compared to conventional statistics. Artificial intelligence (AI) has thus become an ML algorithms have been used to assign patients to high/low-risk groups of recurrence, forecast the risk of cancer in individuals with a genetic predisposition and tailor follow-up and therapeutic interventions (29-33). Additionally, another AI method is natural language processing (NLP), which is used to revamp unstructured medical text into structured data. This allows the extraction of the important clinical indicators in the physician notes, pathology reports or radiology summaries automatically and greatly simplifies the process of diagnosis (34, 35). From screening asymptomatic patients with help of CNNs and Transformers to understand the risk of breast cancer and identifying various types of cancer with the help of the analysis of cfDNA, AI improves early diagnosis and individualized prevention. It helps in molecular profiling of tumors, e.g. glioma subtyping by histopathology, deep learning and assists in prognostic modeling in cancer e.g. endometrial cancer in conjunction with combined clinical and omics data. Another critical role of AI is optimizing treatment, such as planning adaptive radiotherapy in prostate cancer or predicting clinical trial eligibility in lung cancer based on electronic healthcare records (EHR) data. Advanced applications are seen in forecasting immunotherapy, finding synergistic combinations of drugs in rare cancers, and designing novel therapies with generative deep learning (Figure 2). Conventional ML methods can still be useful in survival analysis or patient stratification, and NLP can be used to extract insights out of unstructured medical text automatically. The breadth of these applications across six functional categories, including risk stratification to generative drug engineering, has been encompassed in Table 1 that act as roadmap in the further sections.

## Role of AI in Cancer Screening

The role of cancer screening is at the forefront of cancer prevention and early intervention. By applying AI based models, there has been a demonstration of an effective approach in screening efficacy of discovering subtle signals that could otherwise be missed by human detection. AI may enhance the precision of screening in asymptomatic populations and adjust screening to risk profiles of patients, overcoming the weaknesses of a one-size-fits-all strategy (36, 37). Real-time AI-based decision support tools can help in solving clinical issues, including differentiating between benign and malignant lesions, identifying tumor margins in surgery, or identifying early recurrence. Also, AI can be used to optimize workflow such as prioritization of high-risk patients, initiating early referrals, and automating tasks in understaffed environments that consume resources (38, 39). Moreover, AI incorporation into prognosis and treatment planning in cancer therapy allows the combination of various data, including tumor genomics, radiologic images, and clinical history, into predictive algorithms to enhance personalized cancer treatment. Precise prognosis helps in shared decision-making, treatment plan tailoring and enhanced patient counselling(40-42).

Multi-modal screening has been improved since AI systems have proved to be effective in various screening areas. DL-models (e.g., CNNs) are mainly used to improve imaging-based screening (e.g., mammography, colonoscopy, endoscopy, dermoscopy). These models automatically acquire spatial and contextual patterns of high-resolution images and detect cancerous features with accuracy that can often match that of expert clinicians (38, 43, 44). Genomic-based screening utilizes ML to analyze gene mutations, expression, and circulating tumor DNA (ctDNA). The use of logistic regression with the LASSO penalty, semi-supervised ensemble models, and neural networks have enhanced the early detection of lung cancer and hepatocellular carcinoma through the detection of high-risk signatures in blood-based tests (45-49). Histopathological and cytological analysis, traditionally based on a manual review, is being quickened and improved with the assistance of automation-based screening with the help of AI models. Such methods are promising in cervical intraepithelial neoplasia and carcinoma of the Barretts esophagus with consistent and fast high-scale measurements (50-52). Pattern recognition of laboratory tests has become an alternative and yet powerful screening option. In a single study, a collection of DL and ML algorithms correctly identified the manifestation of a variety of illnesses such as cancers based on regular lab reports, indicating the opportunity of AI in opportunistic screening (53, 54). There are various ways of validating AI models used in screening: external datasets, stratified cross-validation, clinical trials, and real-world comparisons with human interpretation. Although most of the studies remain in exploratory or pilot phases, some of these studies have already completed clinical deployment readiness, such as the Avon-ACRIN mammography trial (55). Key AI screening studies, with the main studies listed by cancer type, data modality and model architecture, are summarized in Table 2. These works employ the use of sophisticated AI-based modalities such as DL, CNNs, ANNs and ML models on a wide range of samples such as Genomic samples, medical images and blood-based biomarkers to screen different types of cancers. An example is Lung-CLiP model, which employs semi supervised learning of the circulating tumor DNA in blood to facilitate noninvasive early diagnosis of lung cancer (56, 57). Major multicenter randomized control trails (RCTs) have used CNNs to analyze images in cervical cytology, colonoscopy and skin lesion detection, which have demonstrated enhanced accuracy and efficiency over traditional algorithms (58-60). Based on the studies as seen in Table 2, there are three common trends: CNNs are predominant in imaging-based screening, genomic and cfDNA models are most effective in the initial phases of lung cancer, and most tools are still in pilot research phase with few progressing into clinical development. This highlights a persistent gap between AI development and routine clinical implementation.

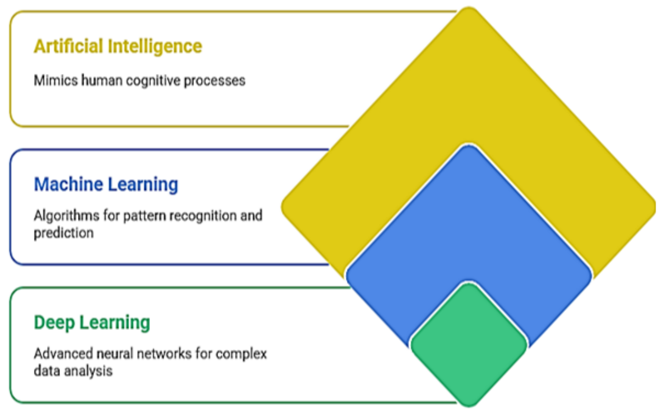


**Figure 1:** Artificial intelligence and its key subfields

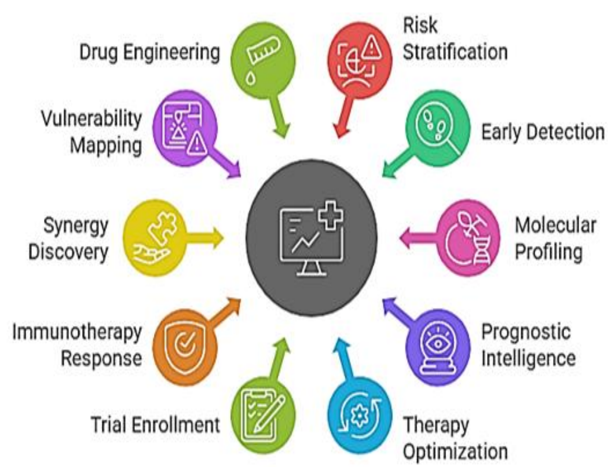


**Figure 2:** Role of AI in Enhancing Cancer Care

**Table 1:** Overview of AI-driven innovations in oncology

| AI Applications in Oncology | Primary Population & Clinical Focus | Data Inputs | AI Approach | Functional Role | Key Output | Validation Type | AI Integration Level | Clinical Readiness | Ref. |
|---|---|---|---|---|---|---|---|---|---|
| **Proactive Risk Stratification & Screening** | Healthy or asymptomatic individuals (Breast cancer screening) | Digital mammograms | CNN + Transformer models | Risk scoring for future cancer onset | 5-year individual cancer risk projection | Retrospective, multi-cohort, global | Emerging decision support tool | Moderate (pilot screening programs) | (37, 38) |
| **Intelligent Early Multi-Cancer Detection** | Symptomatic patients or high-risk groups (Multi-cancer detection) | Circulating cfDNA signatures | Supervised ML classifiers | Signal detection + tumour origin mapping | Binary cancer presence + tissue localization | Case–control, prospective | Diagnostic aid under validation | High (Biotech commercialization) | (39) |
| **Histologic & Molecular Tumor Profiling** | Biopsied cancer patients (Gliomas / brain tumours) | Histopathology (H&E) slides | CNN + autoencoder + MLP ensemble | Tumor class/subtype prediction | Epigenomic (methylation) tumour classification | Retrospective | Research utility in genomics labs | Moderate (specialized diagnostics) | (40) |
| **Prognostic Monitoring** | Diagnosed cancer patients Endometrial cancer follow-up | Integrated data (clinical, imaging, omics) | Hybrid deep learning models | Disease progression and relapse risk assessment | Likelihood of distant recurrence | Historical patient cohort-based | Early adoption in predictive analytics | Low–Moderate | (41) |
| **Adaptive Therapy Optimization** | Radiotherapy candidates (Prostate cancer radiotherapy) | CT scans + anatomical segmentation | Random Forest, rule-based ML | Personalized treatment design | Voxel-level radiation dosing map | Prospective studies | AI-assisted clinical planning | High (Pilot integration in hospitals) | (42) |
| **Precision Trial Enrolment** | Oncology trial populations (Lung cancer trial refinement) | Electronic health records (EHR) | Classical ML models | Inclusion/exclusion criteria tuning | Predicted hazard ratios with eligibility shifts | Retrospective modelling | Trial protocol augmentation | Moderate | (43) |
| **Immunotherapy Outcome Prediction** | Research subjects / patient-derived models (Melanoma immunotherapy) | Gene expression profiles | Cox regression + ML filters | Immunotherapy outcome prediction | T-cell exhaustion/dysfunction score | Retrospective omics study | Exploratory biomarker discovery | Low (Preclinical tool) | (44) |
| **Therapeutic Synergy Discovery** | Drug development environments Rare cancers (combinatorial therapy) | Drug pair compound data | Large Language Models (LLMs) | Predictive synergy modelling | Drug combination efficacy ("Yes"/"No") | In vitro pharmacological testing | Early-stage computational screening | Low | (45) |
| **Functional Vulnerability Mapping** | Experimental tumour models (Ovarian & colorectal cancer) | Single-cell RNA sequencing | CNN + logical ML architectures | Synthetic lethality target identification | Functional gene logic gates (AND, OR, NOT) | In vitro discovery pipelines | Preclinical genomic exploration | Low | (46) |
| **Generative Drug Engineering** | Preclinical discovery labs (Multi-cancer therapeutic targets) | Structural antibody datasets | Generative DL (e.g., GANs, VAEs) | De novo therapeutic design | Engineered antibodies with high affinity | In vitro antibody validation | Advanced AI in early-phase R&D | Low | (47) |

**Table 2:** Applications of AI in screening various types of cancers and neoplasms

| Cancer Type / Condition | Study Type & Trial Registration | Sample Size / Dataset | AI Tool / Method | Data Modality | Methodology Used | Model Type | Validation Strategy | Screening Phase | Clinical Readiness | Key Findings / Impact | Ref. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Lung cancer (gene-based) | Retrospective (No trial ID) | 255 gene signatures | Lung-CLiP with semi-supervised learning | Circulating cfDNA (genomic features) | Genomic Profiling | Ensemble (3NN, NB, LR, DT) | Orthogonal mutation validation in WBCs | Early detection | Research-only | Enhanced genomic stratification of lung cancer risk | (68) |
| Lung cancer (genomic profiling) | RCT (NLST) | 2,511 individuals | LASSO-regularized logistic regression | Whole-genome sequencing | Genomic Profiling | Logistic regression (penalized) | Independent external validation cohort | Early detection | Advanced research | Identified high-risk profiles using mutational signatures | (69) |
| Cervical intraepithelial neoplasia (CIN) | Multicenter (ChiCTR2000034121) | 188,542 cytological images | DL-based AI cytology system | Pap smear (microscopy) | Cytology Imaging | CNN-based DL | F1-score optimization | Initial screening | Pilot-ready | Outperformed manual screening in detection accuracy | (73) |
| Cervical precancer | Multicenter (ID missing) | 60 patients | AI-optimized diagnostic interface | Colposcopy imaging | Colposcopy | CNN | External hospital dataset | Follow-up screening | Research-only | Demonstrated superior lesion identification | (74) |
| Colon cancer | Multicenter RCT (NCT04422548) | 112,199 colonoscopy frames | CNN-based polyp detection tool | Colonoscopy video | Colonoscopy Imaging | Deep CNN | Independent 40k-image set | Live screening | Pilot stage | Improved adenoma detection rate (ADR) vs standard colonoscopy | (70) |
| Colorectal cancer (Lynch syndrome) | Multicenter observational (DRKS00023157) | 96 Lynch syndrome patients | AI-assisted colonoscopy navigation | Endoscopy images | Endoscopic Imaging | CNN | Exploratory only; no RCT yet | Targeted high-risk screening | Early feasibility | Initial results show better lesion detection sensitivity | (75) |
| Skin neoplasms | Multicenter (ID missing) | 576 cases | AI-assisted ceroscopy analysis | Dermatoscopic images | Dermoscopy | CNN | Asian Fitzpatrick skin type–focused study | Opportunistic screening | Prototype | Increased melanoma and carcinoma detection in underrepresented phototypes | (72) |
| Cervical cancer screening via AI colposcopy | Multicenter (partial data) | 60 patients | AI-optimized diagnostic interface | Colposcopy imaging | Colposcopy Imaging | CNN | External hospital dataset | Follow-up screening (secondary screening) | Research-only | Superior lesion identification; overlaps screening use | (71) |
| Multi-disease prediction | Not trial-based | 5,145 cases, 326,686 tests | DL ensemble with XGBoost & LightGBM | Routine lab records | Laboratory Data | DNN + ML ensemble | Fivefold CV + validation loss scoring | Opportunistic screening | Feasibility stage | Detected disease patterns from routine diagnostics | (76) |
| Lung nodule segmentation | NLST + NELSON trial scans | 888 low-dose CTs | Volumetric segmentation NN | CT imaging | Chest CT Scan | Neural network | 50-scan cross-evaluation | Screening workflow enhancement | Advanced research | Automated lung nodule sizing with high precision | (77) |
| Breast cancer (mammography) | Multicenter RCT (Avon-ACRIN) | 1,163,147 women | AI-integrated mammogram analysis with density quantification | Mammographic images | Mammography | Deep CNN | 2,222 interval cancer follow-up | Routine screening | Clinical testing | AI aided early-stage cancer detection in high-volume datasets | (78) |

## Artificial Intelligence in Cancer Prognosis

Cancer prognosis, the ability to predict disease recurrence, progression and patient survival is a critical component in informing therapeutic decision making (14). Clinicians had been using the conventional prognostic models which included TNM staging system, Cox regression, Kaplan-Meier survival curves or logistic regression (61). These techniques, however, are frequently unable to cope with the complexity and high dimensionality of multi-omics, radiological and clinical data. In this regard, AI, specifically ML and DL, is evolving prognosis, as it allows making more personalized and precise predictions (62, 63). As the field of oncology has embraced the power of big data, such as through genomic profiles, imaging, pathology and electronic health records, AI models have demonstrated an unprecedented ability to handle this complexity.

ML algorithms, including Support Vector Machines (SVM), Decision Trees (DT) and Random Forests (RF); and DL models, notably ANNs and Deep Neural Networks (DNNs), are trained using large sets of data to make predictions, including probability of recurrence, time to progression, overall survival, and response to therapy. These algorithms can identify non-linear relationships and high-order interactions between variables that are not always noticeable by human reasoning as with traditional methods (64-66). ML methods in prognosis are: i) SVM for binary classification (e.g., survivors vs. non-survivors) with high accuracy ii) Random Forest (RF) models, which can cope with missing values and non-linearity among variables, which is ideal in noisy clinical datasets, iii) Gradient Boosting Machines (GBM) have demonstrated better results in SEER datasets with enhanced dynamic learning performance (67-69).

DL approaches in prognosis are: i) Multimodal-DNNs integrate heterogeneous data such as imaging, gene expression, and clinical records to enhance predictive performance. ii) Cox-net, a hybrid of ANN and Cox regression, uncovers biologically meaningful features while predicting survival. iii) Survival Recurrent Networks (SRNs) outperform TNM staging by considering temporal and individual-level variations in survival prediction (70-72). Moreover, combining traditional statistical tools with AI Hybrid and Ensemble models can lead to higher predictive power. For instance, combining genetic algorithm (GA) for feature selection with boosting trees (e.g., GAOGB) or using ensemble voting classifiers such as RF + ANN + SVM shows improved performance (73, 74).

## Application of AI Tools in Oncology

AI in Breast cancer prognosis has matured significantly in different studies. Sun et al. proposed a multimodal DNN architecture integrating gene expression and clinical data achieving high AUC (75). Sahu *et al.* applied PCA with ANN for early-stage breast cancer classification (76). Delen *et al.* found Decision Trees outperform ANN and logistic regression on SEER data (77). In gastric cancer, ANN models outperform Cox regression for survival prediction. Studies show ANN's true prediction rates exceed 83%, compared to 75% for Cox models (78). SVM and DL models using MRI radiomics and genomic features (e.g., IDH mutation status) are yielding survival predictions with AUCs > 0.90 in Glioma and glioblastoma (TCGA-based cohorts) (79). Studies of Lung and Ovarian Cancers highlighted that the combination of PET/CT radiomics with ML (SVM, RF) enhances restaging and outcome prediction. Ovarian cancer prognosis using hierarchical clustering and SVM reveals new molecular signatures (80, 81). Several studies integrating AI techniques across different cancer types, highlighting key technical aspects and outcomes, are summarized in Table 3. The datasets provided in Table 3 originate from different countries and sources such as hospital records, SEER and TCGA. Data types include clinical, genomic, transcriptomic, imaging and multimodal inputs. Accuracy, area under the curve (AUC), sensitivity, specificity, and concordance indices are primary reported performance metrics showing improvements over conventional statistical models. Notably, some studies highlight the use of advanced imaging-based models for personalized prediction, stage-specific modelling for improved accuracy, and the integration of multi-dimensional data for improved prognosis. The increasing complexity and efficacy of AI in cancer diagnosis and prognosis across diverse datasets and contexts is highlighted by this compilation.

## Artificial Intelligence in Cancer Diagnosis: Transforming Clinical Precision

Cancer is among the most complicated and deadly diseases worldwide having more than 100 types that took the lives of about 10 million people in 2020 (1). Although medical research has improved, early and accurate diagnosis is a challenge because of heterogeneity of tumors, their dynamic progression and variability in diagnostic techniques by various clinicians. AI has become a groundbreaking solution in the field of oncology, as it has improved the accuracy, speed, and consistency of the diagnostic process of various types of cancer (82). The diagnosis of cancer frequently involves multidisciplinary data such as radiological imaging, histopathological slides, clinical data and molecular profiles. The conventional diagnostic methods are not effective in handling this heterogeneity. AI models, especially based on ML and DL, are able to identify complex patterns in large and non-linear data to minimize errors in diagnosis, improve prediction models, and identify abnormalities at early stages (42, 83). Radiology and imaging modalities by AI ranging from CT, MRI, PET, and ultrasound plays a pivotal role in cancer detection (84). The AI system known as AI-powered CADe (Computer-Aided Detection) can identify the lesions or abnormalities that the human eye cannot see and detect (85). AI-based deep CNNs are highly sensitive in minimizing false negative outcomes and in detecting subtle radiographic changes in lung and breast cancer (86). Artificial intelligence applications such as U-Net, ResNet and Faster-RCNN are used to enhance the specificity of diagnosis, better tumor segmentation and anatomical location of tumors in MRI and CT images (87, 88). AI-supported digital pathology enables analysis of histological slides automatically. Algorithms that have been trained on hematoxylin and eosin-stained biopsy slides, like those employed in the diagnosis of prostate and colorectal cancer, have improved diagnostic reliability significantly (89-92). AI can grade tumors, identify invasion patterns, and detect rare cell types with high accuracy, often matching or exceeding expert pathologist performance (93).

**Cancer Specific Diagnostic Innovations by Artificial Intelligence**

In skin cancer CNNs, trained using more than 129, 000 images, are capable of recognizing melanomas (94). Complex lesion structures can be segmented with reinforcement learning and DBNs (Deep Belief Networks) (95). AI apps on smartphones such as SkinVision can provide self-diagnosis with 95% accuracy in early diagnosis (96). The segmentation of CT scans that are enhanced by AI e.g., U-Net, PSPNet is instrumental in detection of early lung nodules in lung cancer (97). ANN-based AI models in lung cancer have demonstrated impressive performance, with up to 95.7% sensitivity and 93.5% specificity (98). NLP algorithms are being incorporated in the imaging reports of lung cancer to improve contextual interpretation (99). Breast cancer diagnostic AI methods such as Ultra-Wideband (UWB) and Probabilistic Neural Networks (PNN) models demonstrate over 98% accuracy at early stages (100, 101). Besides, hybrid algorithms ESO-GSO (Eagle Strategy Optimization- Gravitational Search Optimization) have been used to optimize features/data to increase the accuracy of the classification using the Wisconsin Diagnostic Breast Cancer (WDBC) dataset in breast cancer (102). AI-assisted histopathological analysis in Prostate cancer shows a significant increase in Gleason grading accuracy and AUC values (up to 0.997) exhibiting strong performance of differentiating cancer grades and patterns (103). One example of AI application in colorectal cancer is Faster-RCNN with ML classifiers, which can identify dysplasia and malignant features of whole-slide colonoscopy on images (104). In gastric cancer, AI models help in the detection of Helicobacter pylori, evaluation of the depth of invasion and risky features through endoscopic images (105). The latest AI applications in cancer diagnostics have been utilized in three major areas, namely: imaging-based diagnostics, genomic-based diagnostics, and liquid biopsy-based detection, which are all summarized in Table 4. It mentions several AI modalities and models, including CNNs, DL and radiomics, which are used with different types of cancer with the help of large datasets, including medical images, genomic sequences and blood biomarkers. Key performance indicators (including accuracy, sensitivity, and specificity) are shown together with clinical validation statuses and demonstrate the current development and the difficulties (such as computing requirements, biases in the data, and the necessity of large-scale external validation). In summary, Table 4 shows the scope and depth of the progressive potential of AI to improve cancer detection, diagnosis and individual treatment planning.

**Table 3:** Applications of AI in cancer prognosis across diverse study populations

| Cancer Type | Country / Dataset | N (Patients) | Data Type | AI Techniques | Performance Metrics | Key Findings | Ref |
|---|---|---|---|---|---|---|---|
| **Breast** | China | 1980 | Genomics + Clinical | Multimodal DNN | Improved AUC (not specified) | Multi-dimensional data fusion improves prognosis accuracy | (93) |
| | USA / SEER | 433,272 | Clinical | ANN, Decision Tree | DT: 93.6%, ANN: 91.2%, Logistic Regression: 89.2% | DT outperformed ANN and traditional stats | (95) |
| | USA | N/A | Transcriptomics | Cox-net (ANN-Cox hybrid) | N/A | Revealed rich gene-pathway info, robust prognosis | (89) |
| | China | 295 | Gene expression | SVM-RFE | +34% accuracy, +48% sensitivity | 50-gene signature better than 70-gene model | (100) |
| | India | 4000+ | Clinical | SVM, KNN, DT | Stage-wise accuracy improved vs joint models | Stage-specific ML outperforms global models | (101) |
| | Multi-datasets (SEER etc.) | - | Clinical | GBDT (XGBoost) | 3-year survival AUC: ≈ 0.803 | Effective brain metastasis prognosis | (102, 103) |
| | China | 6477 | Clinical (EMR) | XGBoost | AUC: 0.813; Acc: 0.739; Sens: 0.815; Spec: 0.735 | Outperformed standard indices in survival prediction | (104) |
| **BCBM** | - | - | Real-world clinical data | Grid search, Bayesian Networks | AUC up to 0.90 | High-accuracy 15-year metastasis risk prediction | (105) |
| **Gastric** | Iran | 436 | Clinical | ANN vs Cox Regression | ANN TP: 83.1%, Cox: 75% | ANN better for survival prediction | (106) |
| | Korea | 500+ | Clinical | Survival Recurrent Network (SRN) | High concordance with actual survival | SRN > TNM staging, allows individualized prediction | (107) |
| **Glioma / GBM** | Taiwan / TCGA | 456 | Radio genomic | Improved SVM | Accuracy: 81.8%, AUC: 0.922 | Accurate glioma survival classification | (108) |
| | India / TCGA | 215 | Genomic | ANN | Accuracy: ~89% | ANN accurately classified glioblastoma outcomes | (109) |
| **Ovarian** | Singapore & Malaysia | 469 | Clinical + Genomic | Fuzzy Forest | Accuracy: 80.6%, Sens: 81.4%, Spec: 76.3% | Good predictor for complex ovarian cancer risk | (110) |
| | UK & Taiwan | 448 | Genomic | SVM + Unsupervised Clustering | HR: 0.64; CI: 95% [0.43–0.95] | Discovered new prognostic gene signature | (111, 112) |
| **Lung** | France | 101 | PET/CT Radiomics | SVM, RF | SVM: Train > RF; RF: Valid 71% vs SVM 59% | RF outperforms SVM in unseen data | (113) |
| | USA / SEER | 10,442 | Clinical | GBM, SVM | RMSE: 32 (GBM), 15.05 (SVM) | GBM is better for long-term survival regression | (114) |
| **Lung (NSCLC)** | Japan | 1,049 | Clinical + Blood biomarkers | XGBoost | 5-yr DFS AUC: 0.890; OS: 0.926; CSS: 0.960 | Strong survival prediction post-surgery | (115) |
| **Lung (NSCLC–BM)** | USA / SEER | 5,973 | Clinical | XGBoost | Accurate 1-year survival prediction | Personalized survival tool for NSCLC with bone metastases | (116) |
| **Colorectal** | UK | 334 | Clinical | 6 Neural Networks | Accuracy: >80%, Sens: 60%, Spec: 88% | Neural networks perform well even in older datasets | (117) |
| | China / SEER | 1568 | Clinical | Semi-random Regression Tree | N/A | Used tree-based model for risk stratification | (118) |
| **Skin Cancer** | TCGA & Hospital | — | Histopathology (eTIL) | ML | AUC: 0.793 | Objective prognostic value from TIL quantification | (119) |
| **Oral Cancer** | Malaysia | 156 | Clinical | Relief-GA-ANFIS Hybrid | Accuracy: 93.81%, AUC: 0.9 | Hybrid model predicts oral cancer prognosis accurately | (120) |
| **Prostate** | USA / TCGA | N/A | Genomic | SVM | Avg Accuracy: 66% | Moderate prediction power, needs further work | (121) |
| | Hospital | — | Imaging | CNN | AUC: 0.939–0.993 | Excellent Ki-67 expression prediction | (122) |
| | Hospital | — | Clinical | RSF + Survival Tree | C-index: 0.64 | Useful predictive model for metastatic prostate cancer | (123) |
| | USA / SEER | — | Clinical | Cox, RSF, DeepHit | C-index: 0.829 (95% CI 0.820–0.838) | High accuracy in 10-year mortality prediction | (124) |
| **Pancreatic** | TCGA | — | Imaging | CNN (HoVer-Net) | — | Imaging pipeline for actionable biomarkers | (125) |
| | SEER | — | Clinical | RF-based nomograms | 3-yr OS AUC: 0.792 | Effective ML nomograms | (126) |
| **Pancreatic Neuroendocrine** | China / SEER | 8422 | Clinical + Genomic | SVM, RF, DL | Accuracy: 81.6% ±1.9%; AUC: 0.87 | DL + hybrid ensemble provides strong prognosis tool | (127) |
| **Spinal Chordoma** | USA / SEER | 265 | Clinical | Boosted DT, SVM, ANN | 5-year survival: 67.5% | Ensemble approach enhances survival estimates | (128) |

**Table 4:** Integrated AI Modalities for Cancer Diagnosis: Advanced Imaging Analysis, Genomic Biomarker Discovery and Liquid Biopsy Technologies for Enhanced Diagnostic Precision

| Modality | Tools / AI Application | Cancer Focus | AI Model(s) Utilized | Dataset Used | Key Performance Indicators | Clinical Status & Validation | Limitations & Considerations | Ref. |
|---|---|---|---|---|---|---|---|---|
| **IMAGING-BASED DIAGNOSTICS** | | | | | | | | |
| **Histopathology (Whole-Slide Imaging)** | CHIEF | Esophageal, gastric, CRC, Prostate | Transformer-based | Millions of WSIs | Accuracy close to 96% | Clinical trials underway | High computational cost, potential dataset biases | (153) |
| | DeepMind AI (Google) | Breast | CNN | 25,000+ scans (UK & US) | Surpassed expert accuracy | Validated in clinical settings | Needs large, annotated data | (154) |
| | University of Pittsburgh AI | Prostate | CNN | TCGA + hospital data | Sensitivity 98%, Specificity 97% | Trail evaluation | Transferability across centers | (155) |
| | Owkin's Models | Mesothelioma | CNN | Multi-institution datasets | Better outcomes prediction | Clinical validation ongoing | Clinical adoption hurdles | (156) |
| | Richard J. Cote AI | Various cancers | DL | Mixed datasets | Improved metastasis risk prediction | Early research | Data sharing/privacy concerns | (157) |
| **Computed Tomography (CT) Imaging** | Radiomics | Lung, Head & Neck | Radiomics + SVM, RF | 1019 CT scans | Enhanced prognostics | Retrospective validation | Limited explainability | (158) |
| | AI Retroperitoneal Sarcoma Grading | Retroperitoneal Sarcoma | CNN + Radiomics | Multi-center cohorts | 82% accuracy | Validation in process | Require external validation | (159) |
| **Magnetic Resonance Imaging (MRI)** | DRONE | Various | DNN | Mixed MRI sources | Sharper Reconstructions | Research only | High computational load | (160) |
| | AI MRI | Gliomas, GBMs | CNN, U-Net | BraTS datasets | Better segmentation | Partial clinical use | Scanner variability issues | (161, 162) |
| **Positron Emission Tomography CT Imaging** | AI PET/CT Lung Cancer Staging | Lung | DL, Radiomics | NLST dataset | More accurate staging | Research stage | Cost + Image quality | (163) |
| **Endoscopy (Narrow-Band Imaging, White Light Imaging)** | AI Colonoscopy | Colorectal | YOLO, ResNet CNN | Endoscopic videos/images | Sensitivity 96.3%, Specificity 93.1% | Multi-system validation | Procedure difference affect performance | (164, 165) |
| **Ultrasound Imaging** | TD-CNN-LSTM LungNet | Lung | Explainable CNN-LSTM | Lung ultrasound data | ~ 96.6% accuracy | Early research phase | Needs testing on other modalities | (166) |
| **GENOMIC-BASED DIAGNOSTICS** | | | | | | | | |
| **Next-Generation Sequencing Variant Calling** | Deep Variant (Google) | NGS | CNN | 1000 Genomes, GIAB | Higher accuracy than conventional methods | Used in clinical & research settings | Compute-intensive | (167) |
| **Proteomics and Protein Structure Prediction** | AlphaFold | Protein folding | DL (Transformer based) | PDB | RMSD improvements | Validated in CASP | Limited to sequenced proteins | (168) |
| **Clinical Decision Support** | IBM Watson for Oncology | Precision Oncology | NLP, ML | Genomic + clinical data | More refined therapy suggestions | Used in hospitals | Limited transparency, bias | (169) |
| **Genomic Risk Profiling** | PRS-AI | Risk Assessment | AI-based PRS | UK Biobank, GWASs | Better risk stratification | Early integration in counseling | Ethical and population bias | (170) |
| **Drug Response Prediction** | AI for Drug Response Prediction | Precision Therapy | ML, Deep RL | GDSC, CCLE | Tailored treatment recommendations | Few clinical trials | Needs stronger validation | (171) |
| **LIQUID BIOPSY AND EARLY DETECTION** | | | | | | | | |
| **ctDNA & CTC-based Cancer Detection** | AI Liquid Biopsy | Multi-cancer | ML, CNN | Large liquid biopsy datasets | Higher early detection accuracy | Some ongoing trials | Lack of assay standardization | (80) |
| **Multi-cancer Blood Test** | Cancer SEEK | Multi-cancer | ML-ensemble | 10k+ patients (Cohort data) | Early detection | Clinical trials | Cost, false positives | (172) |
| **Circulating Biomarker Detection** | Galleri (GRAIL) | Multiple Cancers | DL | 50k+ participants | High specificity detection | Used in screenings | Risk of false positives | (173) |
| **Early-stage Lung Cancer Detection** | Orion | Lung | Semi-supervised VAE | Retrospective + prospective | Sensitivity 94%, Specificity 87% | Ongoing studies | Regulatory hurdles | (174) |
| **Integrated Liquid Biopsy Tools** | AI for Integrated Liquid Biopsy | Breast, Lung, Prostate | DL fusion | Cancer registries | Better multi-cancer detection | Awaiting clinical roll-out | Data heterogeneity | (175) |
| **Exosomal Biomarker Detection** | ASCENDx | CRC | AI-based feature extraction | Multi-center exosome studies | 95.8% sensitivity, 100% specificity | Preclinical | Lack of standardized protocols | (176) |

***DRONE:*** Dual-Domain Residual-based Optimization Network, ***CHIEF:*** Clinical Histopathology Imaging Evaluation Foundation, ***NLST:*** National Lung screening Trail, ***YOLO:*** You Only Look Once, ***LSTM:*** Long Short-Term Memory Network, ***GIAB:*** Genome in a Bottle, ***PDB:*** Protein Data Bank, ***CASP:*** Critical Assessment of Protein Structure Prediction, ***PRS:*** Positional Reasoning System, ***GDSC:*** Genomics in Drug Sensitivity in Cancer, ***GWAS:*** Genome wide association study ***CCLE:*** Cancer Cell Line Encyclopaedia, ***VAE:*** Variational Autoencoder, ***ASCENDx:*** Acoustic Separation and Concentration of Exosomes and Nucleotide Detection

## AI in Cancer Treatment

AI applications in cancer treatment span four major domains: radiotherapy planning, surgical assistance, chemotherapy optimization and immunotherapy. AI plays a key role by predicting effective drug combinations through the analysis of complex protein data. This allows fast identification of therapies that boost clinical results and speed up drug development. While most AI-driven drug combination tools remain in preclinical or early validation stage, several have begun transitioning into prospective clinical assessment. AI is tf radiation therapy by refining treatment planning, dose distribution and adaptive radiotherapy using real-time imaging. This helps to target tumors effectively while protecting healthy tissues (106). In surgery, AI aids image-guided procedures and preoperative planning, which enhances the precision and outcomes of operations. Chemotherapy and immunotherapy also benefit from AI models that forecast how individual patients will respond and help adjust drug regimen to reduce treatment failures. Furthermore, AI facilitates early cancer detection, identifies biomarkers, and improves clinical trial processes (66).

## AI in Radiotherapy and Surgery

AI has increasingly played a significant role in increasing accuracy and efficiency in cancer treatment, specifically in radiotherapy and surgical oncology. In radiation oncology automated target delineation, deformable image registration, and adaptive radiotherapy using AI-based deep learning algorithms have refined treatment against an ever-changing anatomy. For example, auto-contouring based on CNN reduces the number of contours created by a clinician and improves plan consistency. In prostate cancer radiotherapy, AI-driven adaptive planning using daily cone beam CT has been reported to improve tumour control probability (TCP) by 10-15% and reduce normal tissue complication probability (NTCP) by up to 25% compared to conventional planning, based on multi-institutional studies of pelvic anatomy adaptation (107, 108).

The emergence of robotic systems integrated with AI has reshaped cancer surgical procedures by improving precession, providing advanced navigational capabilities during operations and supporting outcome forecasting. When machine learning algorithms are combined with surgical robots like da Vinci platform, surgeons gain enhanced control and reduced hand tremor through intelligent guidance systems. Additionally, the incorporation of computer vision technology alongside augmented and virtual reality interfaces enables surgeons to visualize anatomical structures and blood vessels in real-time during procedures (109). Studies have shown that the technologies have recorded a margin evaluation improvement of about 30% compared to traditional ones with a shorter time of surgery by about a quarter. Similarly, intra-operative imaging and histopathology enhanced by AI can be used to detect metastasis better and effectively locate tumor margins and representative normal tissue with highly accurate diagnostic accuracy of basal cell carcinoma excision during a Mohs surgery (AUROC 0.94) (110, 111). These technological innovations are important in reducing surgical complications, saving time and recovering patients faster and creating a transition to personalized and less invasive treatments of cancer. AI in drug discovery and development.

## AI in Drug Discovery and Development

AI is reshaping the pharmaceutical landscape of treating cancer, as it accelerates the discovery of therapeutic targets, generates molecules and assists in finding the most favorable combinations of the drugs. State-of-the-art computational methods such as deep learning networks, generative adversarial networks (GANs) and graph neural networks (GNNs) have revolutionized the process of creating drugs in the laboratory. These technologies enabled rapid and precise modeling of protein configurations, particularly in ex-vivo drug development paradigms, as demonstrated by AlphaFold2 in high-resolution models of oncogenic kinases and tumor suppressors. Creative AI systems like GENTRL, have pioneered the ability to design entirely new drug from scratch, dramatically shortening developmental timelines i.e., development of a small molecule DDR1 kinase inhibitor in just a few weeks (112, 113).

AI-powered platforms (e.g., DeepDDS), devoted to predicting drug synergy, utilize a rich chemical dataset in conjunction with genomic data from the genome-wide association study to develop drug combinations. Their substantial improvement (~16%) compared to conventional approaches in predicting drug combinations was demonstrated in experimentally validated combinations of paclitaxel and carboplatin in HER2-positive metastatic breast cancer (114). Knowledge graph approaches allow new drug–disease associations to be uncovered in the literature weaved from diverse biomedical data to improve drug repurposing. Application of AI to analyze patient's genetics has enhanced treatment selection process, as evidenced by MINDACT clinical trial, which applied genomic risk classifiers a foundational form of ML-based clinical decision support to demonstrate that approximately half of early stage, HR-positive, HER2-negative breast cancer patients could safely forgo chemotherapy without compromising five year survival (115). Whether using AI for drug discovery, drug development or improving clinical decisions, there are some advances related to the significant temporal streamlining and the improvement of drug repurposing efforts. Overall, AI is expected to further foster rapid drug development by integrating available data from cellular states, integrating maps of molecular targets, predicting chemical properties of compounds/drugs, and making therapeutic precision possible. Thus, by augmenting our traditional approaches and by reshaping the learning opportunities in discovery, development and patient initiation to clinical trials, AI is paving the foundation for personalized clinical oncology care.

## AI in Chemotherapy and Immunotherapy

AI has increasingly become part of the process of optimizing the treatment of chemotherapy and immunotherapy. Examples of AI-based clinical decision support systems (CDSS), such as Watson for Oncology and CSCO-AI, have produced recommended chemotherapy regimens rapidly and based on evidence and with concordance rates over 90% versus expert tumor boards. Integrating multi-omics data, electronic medical records and clinical trial information into AI models enables patient stratification for treatment response and toxicity, allowing customized dose to limit adverse effects. Reinforcement learning approaches also allow the AI models to modify chemotherapy schedules to achieve maximum chemotherapy efficacy while minimizing toxicity (41, 116).

The role of AI includes biomarker discovery research for immunotherapy, where identified data provide insight in predicting which patients will respond to checkpoint inhibitors (CPIs). Tumor mutational burden, neoantigen and radiomic data have been tabulated with AI models, which can provide a significant opportunity in predicting CPI-ed immune-related adverse events. AI technologies such as Tempus use cumulative multi-modal data to offer a customized treatment proposal to real-time patients. It is worth noting that AI has enhanced clinical trial design by filtering eligibility criteria with the use of natural language processing and computer vision, which are used to complicate the recruitment process and enhance the values of the trial sample cohort (117). Combined, these advances can be viewed as demonstrating that AI systems have moved beyond an experiment in a laboratory to a now plausible proven technology to redefine the systemic treatment strategy to cancer, the design of trials on upfront patients

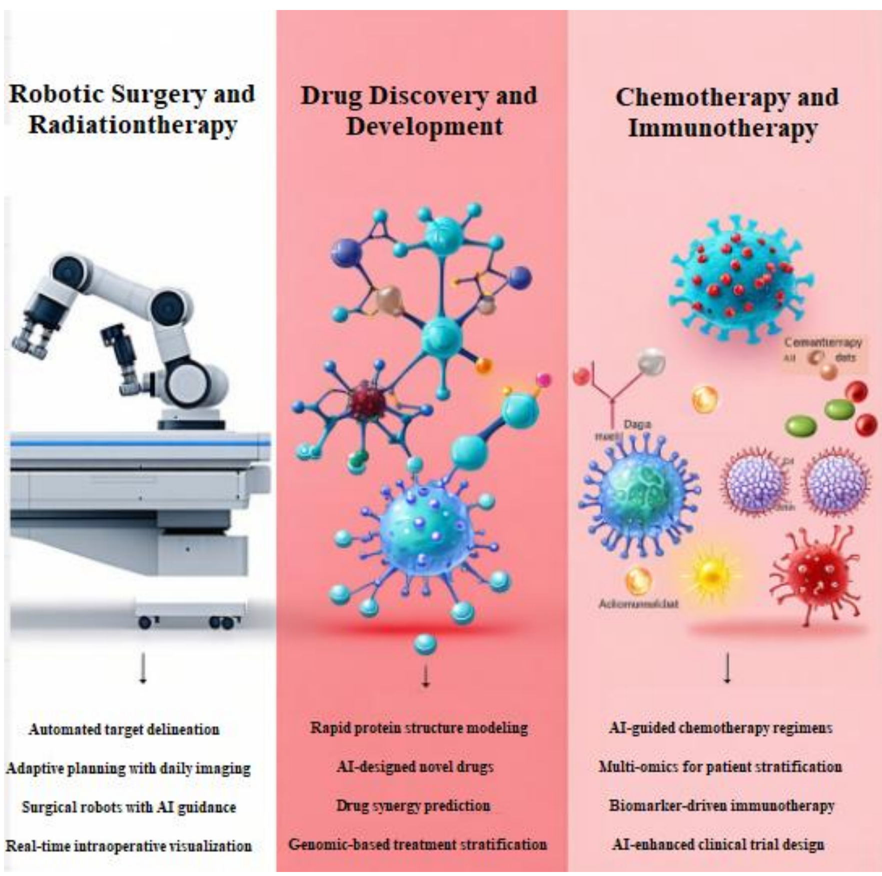


**Figure 3:** Applications of Artificial Intelligence in Cancer Treatment: Robotic Surgery, Drug Discovery, and Chemotherapy/Immunotherapy

## Challenges, Ethics and Implementation Barriers

Despite the excellent technological developments, the issue of transferring AI between research and daily oncological practice is complex due to a range of problems that strengthen each other. One of the most critical problems is the issue of data bias and representativeness: majority of AI models in oncology are trained on datasets that are mostly based on high-income countries with a strong presence of Western institutions, which restricts their applicability to other ethnic, geographic, and socioeconomic groups. The risk of minority groups and rare cancer subtypes being underrepresented will lead to the continuation and intensification of existing health disparities in case the models are implemented without any demographic validation (118). Intimately connected is the issue of external validation: as this review has shown, most AI systems perform well on retrospective and single-institution datasets, but no uniform external prospective validation of the systems across diverse clinical settings exists. The difference between the reported model performance and the utility in the real world cannot be accurately determined without rigorous multi-center trials as well as standardized benchmarking (119).

The so-called model interpretability is the black-box problem that is a great challenge to clinical trust and adoption. Deep learning models, despite being very precise, have minimal or no straightforward interpretation of specific predictions, making it challenging for clinicians to audit decisions, recognize failure cases or corroborate medico-legal accountability (Figure 4). Explainability models like SHAP (SHapley Additive exPlanations) and Grad-CAM provide semi-solutions but are yet to be brought to the norm across oncology AI platforms (120). This has been responded to by the regulatory bodies e.g. the U.S. FDA or the European Medicines Agency (EMA) with special approval schemes on AI-based medical devices; however, the continuously learning and updating nature of AI models, which continue to operate once deployed, presents new challenges to traditional pre-market regulatory models, which require new paradigms to track ongoing performance and post-market surveillance (121).

One of the main ethical considerations is the issue of privacy of data, since AI models rely on extensive amounts of sensitive patient data in the form of genomic profiles, imaging repositories and longitudinal clinical data. Frameworks like HIPAA (USA) and GDPR (Europe) limit -institutional co-operation and data sharing. Additionally, the risk of re-identification and unauthorized secondary use of de-identified datasets raises broader concerns regarding data governance. As a technical mitigation strategy, federated learning has emerged as a promising approach. In this method, models are trained locally without consolidating raw patient data. However, it introduces additional complexity in model aggregation and quality assurance (122). In addition to data governance, the adoption of AI in clinical workflows is still a feasible impediment. Most AI tools have been created without considering the clinical contexts where they need to operate, which has caused them to lack interoperability with existing electronic health record (EHR) systems, have been opposed by clinical personnel because of alert fatigue or disruption of their workflow, and have not been adequately trained to make them user-friendly. The participatory design of success in deployment needs to be clinician, informatician, and patient-involved in the earliest phases of development (123).

There are additional cost and infrastructure constraints to equitable AI use, which have been exacerbated by low- and middle-income countries (LMICs) that shoulder an unequally high share of the global cancer burden. Computing infrastructure, extensive annotated training data and expertise in AI are all significant resource needs that might be unavailable to resource-constrained health systems in the predictable future. It is an ethical requirement that AI-driven oncology progress not only be biased towards well-resourced contexts, but that the design, funding and dissemination plans of future AI studies incorporate this requirement (124, 125). Together, overcoming these obstacles with the help of interdisciplinary cooperation, the fairness with which datasets are built, transparent model development and flexible regulatory frameworks will be vital in unlocking the full potential of AI in oncology.

## The Future of AI in Cancer

Cancer has remained a major problem in the global health context as it has been diagnosed worldwide at rates of about 19.3 million and almost 20 million in 2020 and 2022, respectively. It is projected that these numbers will skyrocket to the point that by 2040, there may be 30.2 million and by 2050, 35 million. It is expected that emerging technologies will integrate AI and digital patient replicas to establish personalized simulations to monitor disease progression and treatment reactions in real-time (1, 126). The next generation will combine AI + Digital Twins, which will allow simulation of cancer progression and therapy outcome in real-time and with patient specificity. The future of screening technologies will probably involve a combination of data streams that incorporate medical imaging, genetic data, patient history, and lifestyle data into an all-encompassing diagnostic system. It is anticipated that healthcare facilities will regularly use instant decision-making tools that can supplement physician knowledge and reduce diagnostic delays, which will fundamentally alter the detection and treatment of cancer in clinical practices.

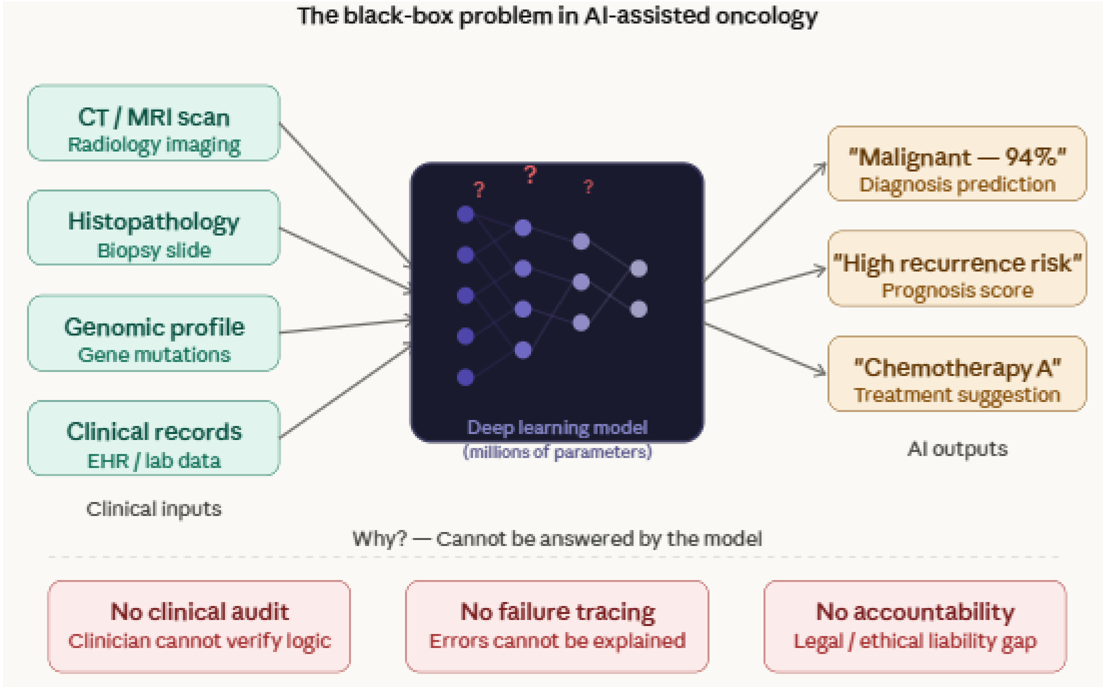


**Figure 4:** Black-box problem in AI-assisted oncology

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