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RECENT AI TECHNOLOGIES IN CANCER DETECTION AND TREATMENT

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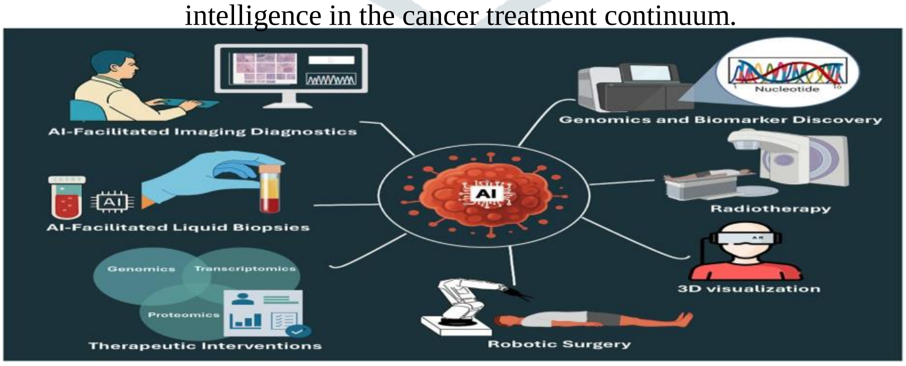
ABSTRACT

Cancer continues to be a significant international health issue, which demands the invention of new methods for early detection, precise diagnoses, and personalized treatments. Artificial intelligence (AI) has rapidly become a groundbreaking component in the modern era of oncology, offering sophisticated tools across the range of cancer care. In this review, we performed a systematic survey of the current status of AI technologies used for cancer diagnoses and therapeutic approaches. We discuss AI-facilitated imaging diagnostics using a range of modalities such as computed tomography, magnetic resonance imaging, positron emission tomography, ultrasound, and digital pathology, highlighting the growing role of deep learning in detecting early- stage cancers. We also explore applications of AI in genomics and biomarker discovery, liquid biopsies, and non-invasive diagnoses. In therapeutic interventions, AI- based clinical decision support systems, individualized treatment planning, and AI- facilitated drug discovery are transforming precision cancer therapies. The review also evaluates the effects of AI on radiation therapy, robotic surgery, and patient management; including survival predictions, remote monitoring, and AI- facilitated clinical trials. Finally, we discuss important challenges such as data privacy, interpretability, and regulatory issues, and recommend future directions that involve the use of federated learning, synthetic biology, and quantum- boosted AI. This review highlights the groundbreaking potential of AI to revolutionize cancer care by making diagnostics, treatments, and patient management more precise, efficient, and personalized.

Keywords: Cancer, Artificial intelligence (AI), Machine learning (ML), Cancer diagnosis, Deep learning (DL)

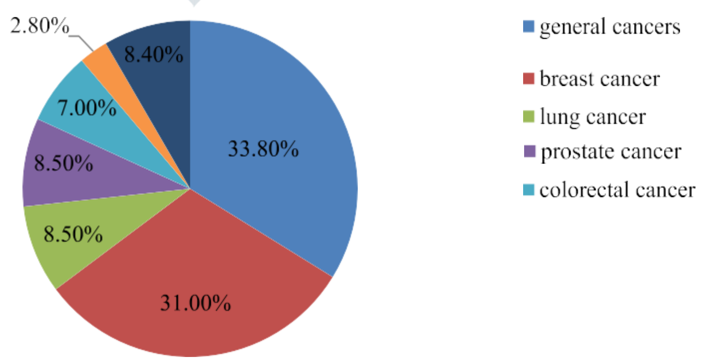
Graphical Abstract: This graphical abstract schematically illustrates the progressive role of artificial intelligence in the cancer treatment continuum.



1. INTRODUCTION

Cancer, an illness that can affect people from all walks of life, is an intricate worldwide health concern that continues to require attention. Cancer is a disease that affects people regardless of age and causes suffering all around the world. Cancer is the second most prevalent cause of mortality worldwide, accounting for one in six deaths in 2020, according to the World Health Organization. Through a gradual accumulation of biological and therapeutic knowledge which accelerated with the development of molecular-cell biology and genetics in the second half of the twentieth century, modern medicine altered that perspective. Together with more-recent technological developments, this progress has made it possible to comprehend the disease in ways that were never possible before. The term "cancer" now encompasses hundreds of different kinds of diseases with similar basic characteristics. Beyond figuring out a particular cancer type’s genetic fingerprint and molecular composition, we now know how crucial the systemic and local tumor environment is to the disease’s progression and presentation. In recent years, interactions between the immune system and the immunological tumor micro environment (TME) has particularly garnered notice.
A normal cell, responds to the signals given by the body either to grow, divide or to die as a natural process. When a varied lifestyle impacts and alters the genetic environment, the said natural process of the cell is disturbed. This change results in unintended actions of the cell like ignoring the signals of the body to stop dividing or to die, to grow in the absence of signals, tricking the immune system, to invade other parts of the body, etc. This process of multiple mutations (changes) in the cell may lead to cancer cells. These abnormal cells grow and divide in the tissue in which they originated, resulting in a mass of cells called a tumor. This tumor may even spread to other parts of the body. One in six people are dying with cancer as per the statistics. Blood tests, biopsy, and imaging techniques help diagnose cancer. A non-invasive way to diagnose and monitor several clinical conditions is through medical imaging. Artificial intelligence (AI) in medical imaging helps screening large amounts of data and reduces the pressure on radiologists.
Artificial intelligence (AI) is a technology that involves the use of algorithms and mathematical models to analyze and process large and complex information. Diagnosis, patient response analysis of the disease before and after treatment, etc. are some of the clinical applications of AI. AI in medical imaging helps improve diagnostic accuracy and efficiency. According to statistics, at least 5% of out patients experience diagnostic error that leads to death in about 10% of these. Due to the rise in the amount of data that is being processed, it takes longer time for both clinical and laboratory analysis. AI helps to analyze data in a short duration of time, which helps faster diagnosis and treatment. AI replaces the routine detection process of radiologists and frees up their time to consult more patients. Various AI algorithms are used to identify the organ, its disease, and severity. Continuous monitoring of a patient’s medical condition from time to time helps effective therapy. However, few factors contribute to the slow adoption of AI in healthcare. They require strict regulatory requirements that hinder implementation of new technologies. The new algorithms require heavy clinical trials for reasonable accuracy and efficiency. Features that AI can extract from a medical image include the size, shape, and texture of the organ or tissue. It can recognize abnormal ties in growth, dimension, and thickness to detect diseases and tumors. Due to a varied patient population, developing an AI model with salient features is a challenging task. The main objectives of the review include application of AI in medical imaging for cancer diagnosis and staging. Assessing the radiological images of any disease is a whole visual task. AI strides to present a qualitative interpretation of cancer diagnosis as analyzed by the radiologists. Not only AI is used to identify the locations of cancer but also to classify and grade the stages of cancer. AI also interprets images of various modalities to interpret the clinical workflow of detection, constant observation, and therapeutic suggestions. To understand the complex structure of cancer cells, AI models are trained based on feature extraction. Modeling an AI can be done using machine learning and deep learning algorithms. Machine learning algorithms self-train themselves to interpret and analyze the given data through various patterns. Deep learning techniques, also a part of machine learning, interpret the data from the perspective of the human brain. Though AI helps easy cancer interpretation, it also faces major challenges which are legal and ethical. Availability of large datasets that are not standardized as it requires experienced medical professionals to validate the results. The data that is given to the ML (Machine Learning) and DL (Deep Learning) models doesn't directly give the output but needs feature extraction, processing the data, and validation. Highly training the models, also leads to inaccurate results. Anticipating the reasons for the failure of the model is also hard to communicate.

Figure -1: **AI implementation in cancer according to the statistics**



Various Types of Cancer

Cancers originating from various cells or tissues may be of many types. This section elaborates some of the existing and most prevalent cancers. Figure 2a, b give details of statistics of different cancers based on gender. The graphs show the incidence of most prevalent cancers in men and women. From the graph it is evident that certain cancers like prostate and lung have higher incidence rates in men. And also breast cancer accounts for the highest percentage amongst women out of all other cancers.

Prostate Cancer

The most prominent life-threatening cancer in males is prostate cancer. As per the statistics of WHO (World Health Organisation), 2020, new cases of prostate cancer are about 1,414,259. It constitutes about 7.8% of all cancers. One in forty men dies because of this. It is the fifth leading disease of cancer worldwide. More than 90% of patients, who are detected with early diagnosis, respond to medication and get fully recovered. The diagnostic procedures available to identify the cancer are biopsy, Tran's rectal ultrasound, CT (Computed Tomography), and MRI (Magnetic Resonance Imaging). MRI is likely to be used to define the progress of cancer. Another way to diagnose is the analysis of his to pathological images of the prostate tissue. These images are graded according to the Gleason factor based on the appearance of the cells in a microscopic view. However, risk factor analysis based on the Gleason factor was found to be ineffective due to the slow growth of cancer. The International Society of Urological Pathology 2014 revised the terminology of differentiating five grade groups based on the Gleason factor.

Bladder Cancer

As per the statistics of WHO, 2020, bladder cancer constitutes 3.2% of all the cancers. The bladder is a hollow organ responsible for the storage of urine in the abdomen. The muscular walls of the bladder are responsible for expanding to store urine and squeeze to throw urine out of the body through the urethra. Common bladder cancer occurs in kidneys or in the bladder itself as the urothelial cells responsible for this cancer are found in the inner layers of the bladder and also in the uterus in females, connecting the bladder and the kidneys. It starts from the innermost layers of the bladder which is at an early stage and when diagnosed is mostly treatable. This cancer grows into deeper layers (advanced stage) which are difficult to treat. If left untreated it spreads to outer layers and also nearby lymph nodes and other organs. Recurrence of the cancer is also possible even after proper treatment. Hence cases of this cancer need to be diagnosed regularly. Depending on the type of cells affected, bladder cancers are classified as urothelial carcinoma, squamous cell carcinoma, and adenocarcinoma. Based on the layers affected, the cancer is also distinguished as non-muscular invasive, muscular invasive and metastatic bladder cancers. The imaging technique preferred to detect bladder cancer is MRI. Performing MRI is considered to be a challenging task due to, variations in bladder size, shape, and intensity in homogeneity of the urine in the bladder also causes shading effect.

Lung Cancer

The air when inhaled through the nose enters the lungs from the windpipe. In the lungs the air is carried through pipes called bronchioles and finally into air sacs called alveoli. Multiple divisions of cells on the inner lines of bronchioles are responsible for lung cancer or lung carcinoma. In some cases, it is caused by the cancerous cells that spread from other organs to the lungs. Lung cancer ranks as the second most prevalent cancer all over the world and occur pies 12.2% out of all the cancers. Statistics of WHO reports 2,206,771 new cases of lung cancer in 2020. Lung cancer mostly occurs in subjects addicted to smoking. Lung cancer is differentiated as small cell lung cancer (SCLC) and non small cell lung cancer (NSCLC). Almost 80% of lung cancer cases fall under NSCLC and 10–15% under SCLC. Based on the type of cells and their area of existence, NSCLC cancer is grouped as squamous cell carcinoma, adenocarcinoma, and large cell carcinoma. Lung cancer is differentiated into four stages based on the size and outspread of the cancerous cells. Chest X-ray, CT scan, PET-CT (Positron Emission Tomography / Computed Tomography), and biopsy are the diagnosing techniques used to find lung cancer.

Liver Cancer

An important primary organ of the body responsible for digestion and storage of nutrients, filtering unwanted materials, etc. is the liver. Because of its salient functions, cancer that affects the liver is also considered fatal cancer. Liver cancer makes up 5% of overall cancer statistics. Mostly cancer in the liver occurs because of the cells in the liver or the cells in the bile duct. Common liver cancers include hepatocellular carcinoma, intrahepatic cancer (10–20% of the cases) and angiosarcoma (rare case of cancer). Similar to other cancers, liver cancer can also be metastatic liver cancer i.e., spread from other organs. However, it is not a very common type of cancer and it stands sixth in place as per the statistics. The imaging modalities used to identify liver cancer is MRI, CT, and ultrasound.

Breast Cancer

The most common cancer in women is breast cancer. The first most prominent of all cancers is also breast cancer. According to the statistics of WHO, in 2020, 2,261,419 new cases were registered, contributing to 12.5% of all the new cases of cancer. If the cells in the breast grow uncontrollably, it results in breast cancer. The cancer starts in the ducts and lobules of the breast. It is differentiated as invasive ductalcarcinoma and invasive lobular carcinoma. Breast cancer spreads to other parts of the body and is said to be metastasized. Some of the breast screening methods include mammography, Clinical Breast Examination, Breast Self-Examination, breast ultrasound, MRI, Digital Breast Tomography and breast biopsy.

Thyroid Cancer

The thyroid is a gland that is responsible for regulating the metabolism of the body. Thyroid cancer develops in the thyroid gland and is mostly curable. It is the fifth most significant cancer in women contributing to about 5.1% of the cancers affecting women. Follicular cells and parafollicular(C cells) cells are the main types of cells present in the thyroid gland. The growth of these cells causes nodules that can be malignant or benign. The main types of cancers in the thyroid are differentiated as thyroid cancer, medullary thyroid cancer and an plastic thyroid cancer. Diagnosis of the tumor or cancer is initially confirmed using ultrasound. The Ti-RADS (Thyroid Imaging Reporting and Data System) score confirms the risk of malignancy. Ultrasound, MRI and PET are some of the imaging modalities to diagnose thyroid cancer.

Kidney Cancer

The primary role of kidneys is to detoxify our blood. Kidney cancer is the most likely cancer in adults above the age of 60. It is a rare cancer (contributing to 2.4% of all cancers) and is curable at its early stages of diagnosis. The uncontrolled growth of the cells at different parts of the kidneys leads to various types of kidney cancer. Kidney cancers are classified as renal cell carcinoma, transitional cell cancer, renal sarcoma, and Wilms tumor. Wilms tumor is mostly observed in children. CT, MRI, ultrasound, and renal mass biopsy are the different ways to diagnose kidney cancer.

Endometrial Cancer

The sixth most affected feminine tumor is endometrial cancer, also referred to as uterine cancer. It contributes to about 6.9% of all cancers affecting women. This occurs in the endometrium layer of the uterus (where fetal growth occurs). Symptoms of this cancer help in early diagnosis, and removing the uterus is the best way to eliminate the cancer. An average of 2.8% of women is diagnosed with this cancer. CT scan, MRI scan, transvaginal, and ultrasound are some of the imaging techniques used to identify cancer. The cancer is diagnosed as type 1 and type 2 endometrial cancers and is also graded as grade 1, grade 2, and grade 3. Grades 1 and 2 come under type 1 and grade 3 under type 2.

Brain Tumor

A brain tumor is an abnormal mass of tissue where cells grow abnormally unchecked by mechanisms that control normal cells. There are more than 308,102 new cases in the year 2020, as per WHO statistics. Tumors may start in the brain as primary tumors or they may spread from elsewhere like muscles, blood vessels, and connective tissues to the brain called secondary tumors. The primary tumors originate from glioma cells, which support nerve cells. WHO graded brain tumors from grade I to grade IV. CT and MRI are imaging techniques that help determine brain tumors.

Colorectal Cancer

The colon is a major part of the large intestine that helps the digestion of food by shattering large molecules of nutrients into those that can be absorbed by the body. The rectum is part of the digestive system that connects the colon to the anus. Colorectal cancer is the second most common cancer in women (9.9% of all women cancers) and third most com mon cancer in men (11.4% of all cancers in men). Colorectal cancer occurs when the colon and rectum grow uncontrolled lably. This is also named polyp. This cancer occurs both in men and women. Early detection and removal of polyp in the colon helps prevent the spreading of cancer to other issues. Colorectal cancers are graded from 0 to IV based on the spread of cancer. It is classified as adenocarcinoma and non-adenocarcinoma. Colonoscopy and MRI are the most implemented screening modalities for colorectal cancer.

Pancreatic Cancer

Pancreatic cancer originates from the organ, pancreas. Pancreatic cancer is always detected at an advanced stage, challenging to treat with the best therapy. It relates to about 2.7% of all cancers. This cancer originates mainly in the ducts of the pancreas. Most of the time, pancreatic cancer is genetic. There are two types of pancreatic cancers. One is exocrine pancreatic cancer, the most common type of cancer and the other is endocrine pancreatic cancer, the rarest type of cancer. CT, MRI, endoscopic ultrasound, and PET (Positron Emission Tomography) are some of the imaging modalities that are used to detect pancreatic cancer.

Cervical Cancer

Cervical cancer is the fourth most significant cancer (6.9% of all cancers) in women. Cervical cancer originates in the cervix, the lower part of the uterus, which connects to the vagina. The most common and highly treatable cancer is cervical cancer. Cervical cancer is staged from 0 to IV. Cervical cancer is a very fast growing cancer. Based on the cells of its origin it is classified as squamous cell, adenocarcinoma, adenosquamous carcinoma, small cell carcinoma, and neu roendocrine tumors. PET-CT, cystoscopy, etc. are some of the diagnostic imaging tools used to identify cervical cancer.

Introduction to AI in the Field of Medicine

The integration of artificial intelligence (AI) in medicine marks a significant shift toward more accurate, personal ized, and efficient healthcare practices, especially in cancer care.

1 AI refers to machines that perform tasks traditionally requiring human intelligence, such as understanding language, recognizing patterns, solving problems, learning from data, and improving performance over time. Key AI techniques include machine learning (ML) and deep learning (DL). ML uses algorithms to identify patterns and make predictions, while DL, a subset of ML, employs multi-layered neural networks inspired by the human brain, such as convolution neural networks (CNNs). Other essential ML techniques include support vector machines (SVMs), decision trees, and K-means clustering algorithms.

In healthcare, AI is applied in diagnostic algorithms; treatment recommendation systems, patient monitoring, and care management tools.AI can process and analyze vast amounts of healthcare data more efficiently than humans, leading to improved diagnostic accuracy, therapeutic interventions, and patient outcomes.

AI-Powered Precision Medicine: Advancing Personalized Treatment

Precision medicine categorizes patients in clinical trials utilizing personal data. The objective is to enhance efficacy and safety outcomes, ultimately increasing the likelihood of clinical success and drug approval. This approach acknowledges that individuals have unique genetic, molecular, and clinical characteristics influencing their treatment responses. Precision medicine aims to enhance treatment outcomes and minimize side effects by tailoring therapies to these individual differences.

AI is vital in precision medicine, as seen in the genomic profiling of tumors that assists in making targeted therapy decisions for patients with breast or lung cancer.AI-driven tools can also facilitate the rapid and accurate interpretation of genomic data, providing real-time recommendations for personalized treatments.AI has been instrumental in genetic analysis by identifying transcription start sites, modeling regulatory elements, and accurately predicting gene expression from genotype data.

These developments are crucial in understanding the relationship between genomic variations, disease presentation, treatment efficacy, and prognosis. In medulloblastoma, AI analysis of numerous exomes has enabled the administration of precise and optimal treatments for pediatric patients. AI-driven precision medicine holds the potential to change cancer care by offering more accurate diagnoses, predicting disease risks before symptoms manifest, and designing tailored treatment plans that prioritize safety and efficiency. Integrating AI into clinical practice is expected to become more widespread as research advances, leading to even more significant advancements in cancer care. Figure 1 illustrates the process of precision oncology.

The Historical Background of AI in Cancer Research

The exploration of AI in cancer research began in the 1970s, with early attempts at computer-aided diagnosis and the development of expert systems. These early AI programs primarily concentrated on diagnosing blood infections, which ultimately laid the groundwork for future medical applications.22 over the years, advancements in computational power, complex algorithms, and the availability of extensive biomedical datasets, have propelled AI from essential pattern recognition to sophisticated ML and DL. These models can identify subtle diagnostic signals in imaging, genomic, and clinical data, significantly advancing cancer diagnosis, prognosis, and treatment planning.

This study aims to review recent advancements and provide future directions for AI-driven oncology, focusing on 4 major fields: medical imaging, pathology, surgery, and drug discovery.

2. LITERATURE REVIEW

The Impact of Artificial Intelligence on Cancer Diagnosis and Treatment: A Review by Niki Najar Najafi , Maryam Azimzadeh Irani and Helia Hajihassani

The complexity of cancer has long challenged the medical community, driving the need for improved early detection and treatment. Artificial intelligence (AI) has profoundly impacted oncology research in recent decades, resulting in innovative diagnostic and therapeutic approaches. This review synthesizes the critical applications of AI in oncology, focusing on 4 key areas: medical imaging, digital pathology, robotic surgery, and drug discovery. We highlight the role of AI in cancer diagnosis and treatment by reviewing key studies and machine learning methods, and we address the field's current technical and ethical challenges. AI models have significantly enhanced the accuracy of medical imaging by efficiently detecting lesions and disease sites, leading to earlier and more precise diagnoses. In digital pathology, AI tools aid in risk prediction and facilitate the examination of extensive tissue sample sets for patterns and markers, simplifying the pathologists' tasks. AI-powered robotic surgery provides different levels of automation, leading to precise and minimally invasive procedures that not only improve surgical outcomes but also lower readmission rates, hospital stays, and infection risks. Moreover, AI expedites the process of discovering cancer therapies by identifying potential lead compounds, predicting drug reactions, and repurposing current medications. In the past decade, several AI-developed drugs have successfully entered clinical trials. These significant advancements underscore the expanding role of AI in shaping the future of cancer diagnosis and treatment. Although standardization, transparency, and equitable implementation must be addressed, AI brings hope for more personalized and effective therapies.

AI technologies in oncology are poised to bring significant advancements, including predictive analytics, targeted delivery, and image analysis. As shown in Table 5, AI-driven tools have demonstrated considerable potential in enhancing diagnostic accuracy, streamlining workflows, and personalizing treatment plans. However, several challenges must be addressed to ensure their reliable implementation in clinical settings.

Present AI models often rely on limited datasets and have primarily undergone retrospective trials for testing. To establish their reliability, these models require further multicenter validation in prospective studies. Although patient outcome assessments are critical for validation in areas like robotic-assisted surgery, there has been a notable lack of research focusing on these assessments, particularly in cancer-related contexts.

The development of AI models must prioritize the use of diverse and representative datasets. For instance, many convolutional neural networks (CNNs) that demonstrate high accuracy in detecting skin lesions are trained on data sets where only 5% to 10% of the participants are Black. This results in a model accuracy for Black individuals that is roughly half that for White individuals, highlighting the critical need for diverse datasets to ensure equitable health outcomes.

The integration of large and diverse datasets is crucial to addressing complex challenges in healthcare. This necessitates collaboration between technology companies and healthcare providers. However, the reliance on medical and personal information underscores the need for robust frameworks to enable secure and anonymous data sharing. One promising approach is federated learning, which processes data locally at each institution. By sharing only model updates instead of raw data, this method effectively preserves privacy and enhances security.

Future statistical studies should optimize workflows to minimize bias, including determining the necessary number of annotations or samples required for robust model training. Additionally, adherence to established guidelines for model reporting, such as the STARD-AI or TRIPOD-AI frameworks, is crucial for ensuring reproducibility and comparability across studies.

A significant concern in AI-driven medicine is the' "black box" nature of many systems. This term refers to models that lack transparency in their input features and algorithms, rendering them difficult to interpret. Consequently, some clinicians hesitate to utilize AI tools, while others may blindly follow AI recommendations without fully understanding the underlying logic, potentially leading to inappropriate treatments. For instance, an experimental study involving 28 pathol ogy experts found that integrating AI improved overall diagnostic accuracy. However, it also resulted in a 7% bias rate, where initially accurate diagnoses were inaccurately altered following AI intervention. Notably, time pressure further amplified the reliance on incorrect AI outputs, underscoring significant risks associated with deskilling and over-dependence on technology.

A recent advancement in addressing the black box problem is the emergence of Explainable AI (XAI). This approach aims to make complex AI logic more interpretable for humans. By employing techniques such as data visualization and model simplification, XAI fosters greater trust and reproducibility in AI models. These developments are critical for enhancing transparency in AI systems, ensuring that users can understand and rely on AI-driven decisions.

Finally, the financial implications of integrating AI into medicine raise significant concerns. For example, hospital wide AI implementation can exceed $36 billion annually, creating challenges for resource-limited settings. Expenses of AI adoption may encompass expensive infrastructure, such as high-performance computing and cloud storage, maintenance, and cyber security measures to protect sensitive genomic and imaging data, clinician training to interpret AI outputs and the cost of rigorous multi-center trials. Consequently, comprehensive cost-benefit analyses and pilot studies are urgently needed to substantiate the case for the widespread adoption of AI in healthcare.

Cancer Detection Using Artificial Intelligence: A Paradigm in Early Diagnosis by Gayathri Bulusu, K. E. Ch Vidyasagar, Malini Mudigonda, Manob Jyoti Saikia

Cancer detection has long been a continuous key performer in oncological research. The revolution of artificial intelligence (AI) and its application in the field of cancer turned out to be more promising in the recent years. This paper provides a detailed review of the various aspects of AI in different cancers and their staging. The role of AI in interpreting and process ing the imaging data, its accuracy and sensitivity to detect the tumors is examined. The images obtained through imaging modalities like MRI, CT, ultrasound etc. are considered in this review. Further the review highlights the implementation of AI algorithms in 12 types of cancers like breast cancer, prostate cancer, lung cancer etc. as discussed in the recent onco logical studies. The review served to summarize the challenges involved with AI application. It revealed the efficacy of AI in detecting the region, size, and grade of cancer. While CT and ultrasound proved to be the ideal imaging modalities for cancer detection, MRI was helpful for cancer staging. The review bestows a roadmap to fully utilize the potential of AI in early cancer detection and staging to enhance patient survival.

The number of cancers, imaging techniques and AI algorithms implemented for early cancer detection were presented in this systematic review. The potential of AI algorithms in radiological assessment provides consistency in analysis and reduces error of interpretation. The review visualized the potential of AI, to analyze huge data rapidly and effectively, competing with human experts. This ability of AI helps assists radiologists for better diagnosis and treatment.

The review was conducted on twelve types of cancers, which are very common. The study revealed the efficacy of AI in detecting the region, size, and stages of cancer. However, choosing correct modality helps AI provide information regarding anatomy and functioning of the organ. An overview of the imaging modalities from the study indicates that, CT and ultrasound are most often used for diagnosis of cancer. MRI and other modalities provide further information of the disease like grading, extent of spread and treatment response. In some cases, PET and PET-CT are also used to obtain the morphological features of the tumor. X-Rays, as mammography were implemented only in the research based on breast cancer. AI was also implemented on images obtained from pathology, colposcopy and biopsy. Finally, direct X-Rays and PET-CT were rarely used for oncological studies.

It was observed that, AI was highly implemented in breast cancer, brain tumors, lung cancer and thyroid cancer detection. A prominent number of AI algorithms, both ML and DL, were implemented in these areas. A moderate level of research as carried out with AI in prostate, liver, kidney and pancreatic cancers. AI in endometrial, cervical and colo rectal cancers was carried out on biopsy, pathological and colposcopy images. A very few MRI and CT images of these cancers were observed. Finally, the research of AI in bladder cancer was rarely found. Only little research was carried out with DL algorithms.

The Application of Artificial Intelligence to Cancer Research: A Comprehensive Guide by Amin Zadeh Shirazi, , Morteza Tofighi, Alireza Gharavi, and Guillermo A. Gomez

Advancements in AI have notably changed cancer research, improving patient care by enhancing detection, survival prediction, and treatment efficacy. This review covers the role of Machine Learning, Soft Computing, and Deep Learning in oncology, explaining key concepts and algorithms (like SVM, Naïve Bayes, and CNN) in a clear, accessible manner. It aims to make AI advancements understandable to a broad audience, focusing on their application in diagnosing, classifying, and predicting various cancer types, thereby underlining AI’s potential to better patient outcomes. Moreover, we present a tabular summary of the most significant advances from the literature, offering a time-saving resource for readers to grasp each study’s main contributions. The remark able benefits of AI-powered algorithms in cancer care underscore their potential for advancing cancer research and clinical practice. This review is a valuable resource for researchers and clinicians interested in the transformative implications of AI in cancer care.

Rapid progress in AI has profoundly impacted cancer research and treatment, leading to enhanced patient outcomes and healthcare efficiency. Incorporating AI algorithms in cancer diagnosis, prognosis, and treatment response prediction has facilitated early detection, customized intervention approaches, and improved overall patient care. In this comprehensive guide, we have explored the crucial role of AI in cancer research, with a specific focus on the applications of machine learning, soft computing, and deep learning algorithms. We have offered an in-depth over view of various algorithms’ functionality and particular applications, supported by pertinent figures and a tabular summary of key findings from each study with the lowest complexity and high suitability for a better understanding of all readers with different backgrounds. The impressive advantages of AI-driven algorithms in cancer care emphasize their potential to reshape cancer research and clinical practice. This review serves as an invaluable resource for researchers, clinicians, and healthcare industry stakeholders, offering insights into AI’s present state and future potential in cancer care.

Future research in AI for cancer care could explore: 1. developing advanced AI algorithms to enhance the precision and efficiency of cancer care. 2. Utilizing multi-modal data (eg, genomic, proteomic, imaging, and clinical reports) to gain a comprehensive understanding of cancer, focusing on AI’s ability to process and analyze such diverse information. 3. Creating personalized treatment plans using AI to consider individual patient characteristics, aiming for treatments that are both effective and have minimal side effects. 4. Leveraging AI in drug discovery to quicken the identification of drug targets and optimize drug designs, potentially speeding up the creation of new cancer treatments. 5. Addressing ethical and regulatory challenges associated with AI in cancer care, such as data privacy and algorithmic fairness, to ensure AI’s responsible use.

Exploring the role of AI in Chemotherapy development, cancer diagnosis, and treatment: present achievements and future outlook By Bassam Abdul Rasool Hassan, Ali Haider Mohammed, Souheil Hallit, Diana Malaeb and Hassan Hosseini

This review aims to explore the role of AI in forecasting outcomes related to chemotherapy development, cancer diagnosis, and treatment response, synthesizing current advancements and identifying critical gaps in the field.

A comprehensive literature search was conducted across PubMed, Embase, Web of Science, and Cochrane databases up to 2023. Keywords included “Artificial Intelligence (AI),” “Machine Learning (ML),” and “Deep Learning (DL)” combined with “chemotherapy development,” “cancer diagnosis,” and “cancer treatment.” Articles published within the last four years and written in English were included. The Prediction Model Risk of Bias Assessment tool was utilized to assess the risk of bias in the selected studies.

This review underscores the substantial impact of AI, including ML and DL, on cancer diagnosis, chemotherapy innovation, and treatment response for both solid and hematological tumors. Evidence from recent studies highlights AI’s potential to reduce cancer-related mortality by optimizing diagnostic accuracy, personalizing treatment plans, and improving therapeutic outcomes. Future research should focus on addressing challenges in clinical implementation, ethical considerations, and scalability to enhance AI’s integration into oncology care.

Artificial intelligence (AI), including its subsets of machine learning (ML) and deep learning (DL), has demonstrated significant potential in transforming chemotherapy development, cancer diagnosis, and treatment. This scoping review highlights AI’s role in improving diagnostic accuracy, optimizing treatment plans, and predicting patient responses, ultimately contributing to reduced cancer-related mortality. However, despite these advancements, challenges remain in integrating AI solutions into clinical practice. Future research should focus on addressing critical gaps such as the incorporation of pharma co genomic and multi-omics data into AI algorithms, which could enhance the precision of personalized medicine. Longitudinal studies are needed to validate the clinical utility of AI-driven predictions and interventions across diverse populations. Furthermore, developing scalable, cost-effective AI systems tailored for resource-limited settings can ensure equitable access to advanced cancer care globally.

3. RESEARCH METHODOLOGY

3.1 The role of artificial intelligence (AI) in modern oncology

AI refers to the wide area of computer science where algorithms or machines are designed to mimic human intellect. In machine learning (ML), a subfield of AI, computers carry out predetermined tasks and use statistical techniques to find hidden patterns in data and enhance model performance. Unlike standard ML, the ML subfield of deep learning (DL) does not rely on human-defined heuristics to complete a task. Instead, DL uses the capability of multilayered neural networks to eliminate manual feature extraction labor and allow for the self-discovery of features that humans are unaware of or would not have expected. The major AI concepts are listed in Table 1. Electronic health record (HER) clinical notes, diagnostic and procedural reports, and other unstructured data are trans formed into discrete data elements using natural language processing (NLP) , an adjacent specialization within AI that aims to bridge human language with machine interpretation . Recent developments in the field have significantly improved the technology's efficacy, allowing it to be used to automate the gathering and recording of patient outcomes, progression-free survival (PFS), and other tumor features associated with cancer. The construction of intricate databases and tumor registries may be facilitated by such automation, which recursively boosts the strength of generated models. NLP has been used to match clinical trials and detect possible adverse medication reactions, either alone or in conjunction with ML/DL approaches. Furthermore, the use of AI for clinical decision-making is thought to improve the likelihood of early disease diagnosis and predictions using high-resolution imaging and new generation sequencing (NGS) methods. Creating sizable datasets and employing specialized bio informatics tools have also resulted in the introduction of novel biomarkers for diagnosing cancer, the development of novel tailored medications, and the delivery of potential treatment regimens.

Category	Concept / Model	Description & Relevance in Oncology
Machine Learning (ML)	Supervised Learning	Learn from labeled data to make predictions. Used for classifying tumors,predicting survival, etc
	Unsupervised Learning	Discovers hidden patterns in unlabeled data; applied in clustering patients or tumor subtypes
	Semi supervised Learning	Combines a small amount of labeled data with a large unlabeled dataset, useful in medical imaging with limited annotations.
	Reinforcement Learning	Learns by trial-and-error through feedback. Applied in treatment policy optimization
	Feature Engineering	The process of selecting or transforming variables to improve ML performance. Crucial for structured EHR and omics data
Classical ML Models	Support Vector Machines (SVM)	Effective in high-dimensional spaces (e.g., gene expression data) for classification tasks
	Random Forests (RF)	Ensemble of decision trees; robust against over fitting, used for biomarker prediction and classification
	Logistic R egression (LR)	Common baseline model for binary classification in survival and risk prediction
	k-Nearest Neighbors(k-NN)	Instance-based learner; used in similarity-based drug repo sitioning and subtype classification

Deep Learning (DL)	Deep Neural Net works (DNNs)	Multilayered feedforward networks for structured data, widely used in survival prediction
	Convolution Neural Networks (CNNs)	Specialized for image data (CT, MRI, histopathology); extracts spatial hierarchies in features
	Recurrent Neural N Networks (RNNs)	Suited for sequential data (e.g., patient records); models time-dependent health trajectories
	Long Short-Term Memory (LSTM)	A type of RNN that captures long-range dependencies; applied in EHR and time-series prognosis
	Gated Recurrent Units (GRUs)	Efficient RNN variant; used in longitudinal cancer data modeling
	R residual Networks (ResNet)	DL architecture with skip connections; enables deeper networks for accurate image-based classification. Exten sively used in digital pathology
	Vision Transformers (ViT)	Transformer-based models adapted for image analysis; increasingly used for WSI (whole-slide image) classification
	LongNet	A transformer variant enabling processing of very long sequences (> 32 k tokens); suitable for high-resolution pathology slide and multi-modal data
	U-Net	A CNN architecture designed for biomedical image segmentation; heavily used in tumor boundary and organ at-risk contouring
	Efficient Net	Optimized CNN with excellent performance at low computational cost; used in real-time image analysis and mobile health apps
	Graph Neural Networks (GNNs)	Models relational data; used for protein–protein interac tions, drug-target graphs, and patient similarity networks
	Autoencoders (AEs)	Unsupervised models for data compression and denois ing; used in omics dimensionality reduction
	Variational Autoencoders (VAEs)	A probabilistic extension of AEs used for generative tasks (e.g., molecule generation)
	Generative Adversarial Networks (GANs)	Generate realistic synthetic data (e.g., histopathology images, molecules). Applied in data augmentation and simulation
	Adversarial Autoencoders (AAEs)	Combines GAN and AE for structured representation learn ing. Used in molecule and feature generation
Transformers And Attention	Transformer	Core architecture using self-attention; enables context aware modeling. Used in NLP and multi-modal integration in oncology
	BERT / Bio BERT / Clinical BERT	Pre-trained language models fine-tuned on biomedical texts. Applied to EHR, radiology reports, and literature mining

Models	GPT / GPT-3 / GPT-4	Autoregressive transformers used for medical Q&A, sum marization, and even synthetic data generation
	T5 / BioT5	Sequence -to- sequence transformers used in molecular- to text or image- to- report tasks
	CLIP (Contrastive Language- mage Pre training)	Joint vision–language model; maps images and text to a shared space. Applied in pathology image captioning and labeling
Learning Paradigms	Transfer Learning	Fine- tuning pre- trained models on domain- specific data. Useful in small medical datasets
	Federated Learning	Decentralized training across institutions without data sharing; supports data privacy in multi-center oncology studies
	Self- supervised Learning	Learns from unlabeled data using pretext tasks. CHIEF and other models use this for pathology image feature extraction
	Contrastive Learning	Learns representations by comparing similar/dissimilar pairs. Enhances embedding quality for histology and radiomics.
	Multi-task Learning	Simultaneous learning of related tasks. Improves generalization in cancer subtype classification and prognosis
Evaluation Metrics	AUROC	Measures model's ability to discriminate between classes; critical in binary cancer detection tasks
	Accuracy, Sensitivity, Specificity	Basic metrics used to assess model performance
	Precision, Recall, F1-score	Balance false positives and negatives; important in imbalanced cancer datasets
	Kaplan–Meier, C- index	Used in survival models to evaluate time- to- event predictions
	Confusion Matrix	Summarizes classification outcomes; visual tool for error analysis

Table 1: Key AI concepts and architectures relevant to cancer diagnostics and research

3.2 Importance of AI in enhancing cancer diagnostics and treatment

Numerous studies have suggested that screening can increase early cancer detection and decrease mortality (Fig. 1). However, even in disease groups like breast cancer where screening programs are well-established, discussions about patient selection and risk-benefit tradeoffs continue, and concerns have been raised regarding a perceived "one size fits all" approach that is inconsistent with the goals of personalized medicine [46–48]. In the near future, AI algorithms may play a part in enhancing this procedure since they can analyze enormous volumes of multimodal data to find signals that would otherwise be hard to spot.

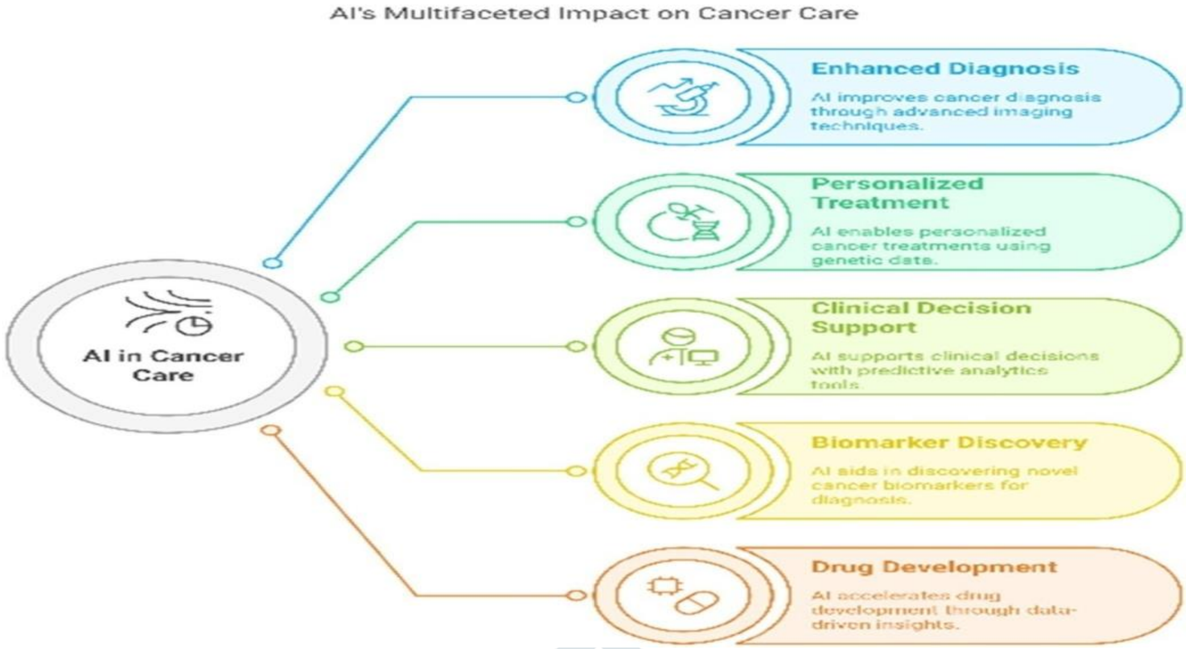


FIGURE-2: **AI's diverse roles in cancer care, including enhanced diagnosis, personalized treatment, clinical decision support, biomarker discovery, and drug development each contributing to improved precision, speed, and outcomes in oncology through data- driven innovations.**

3.3 Objectives and scope of this review

In-depth review of AI's role in modern cancer diagnostics, consolidating diverse cancer types and AI-facilitated diagnostic approaches into a cohesive overview. AI in oncology enhances diagnosis, treatment, and patient management by increasing precision, efficiency, and personalization. Leveraging ML, DL, and NLP, AI analyzes complex datasets—including pathology reports, clinical records, genomic data, and medical images—to generate insights that support more accurate and timely clinical decisions. Its goals include early detection, personalized treatment planning, and streamlined care delivery to improve patient outcomes. This review spans research-driven AI innovations and clinical applications, incorporating stud ies, benchmark models, commercial tools, and regula tory perspectives. It offers valuable insights for a wide audience, including oncologists, AI researchers, informaticians, policymakers, and biomedical engineers. By framing AI as a bridge between predictive and precision oncology, this review supports strategic decision-making and encourages research that translates AI's theoretical promise into real-world clinical impact.

3.4 AI in cancer diagnostics

AI is developing at an exponential rate. Clinical oncology research is now more focused on comprehending the intricate biological architecture of cancer cell proliferation in order to decipher the molecular origins of cancer. In order to address the current situation of rising cancer mortality rates worldwide, it has also concentrated on processing millions of pertinent cases in big data and computational biology. Furthermore, the use of AI in clinical decision-making is thought to improve the like lihood of early disease diagnoses and predictions using high-resolution imaging and NGS methods. By creating sizable datasets and employing specialized bioinformatics tools, it may also result in introducing novel biomarkers for diagnosing cancer, developing novel tailored medications, and delivering potential treatment regimens.

3.5 Imaging - based AI diagnostics

AI, which is based on computational models and bio informatics-based algorithms, presents medical imaging technology (MIT) with significant opportunities for advancement. It can identify biological alterations and aberrant cellular growth in the body. In addition to being crucial in radiology, AI-assisted MIT has had a significant influence on neuro radiography and medical resonance imaging. Numerous dynamic applications of AI exist, including picture interpretation and categorization, data organization, information storage, information mining, and much more. AI is anticipated to greatly assist pathologists in enhancing diagnostic specificity because of its broad application in biomedical imaging technology.

Assessing tumors using traditional radiographic imaging is primarily based on qualitative characteristics, such as tumor density, enhancement patterns, intra-tumoral cellular and a cellular compositions (including blood, necrosis, and mineralization), tumor margin regularity, anatomical relationships with surrounding tissues, and impacts on these structures. It is possible to quantify a tumor's size and shape using one- (1D), two- (2D), and 3-dimensional (3D) analyses. All of these qualitative phenotypic descriptions are referred to as "semantic" traits. In contrast, a quickly developing area known as radiomics is making it possible to digitally decode radiographic pictures into quantitative properties, such as size, shape, and textural pattern descriptors. The automatic quantification of radiographic patterns in medical imaging data has significantly progressed in recent years due to advancements in AI approaches. A subset of AI called DL is particularly promising since it automatically learns feature representations from sample photos and was demonstrated to perform on par with or even better than humans in task-specific applications. DL has shown relative robustness against noise in ground truth labels, among other things, even though it requires enormous datasets for training.

In external-beam radiation therapy, to mographic imaging is vital for follow-up care, image guidance, and treatment planning. A CT simulation is typically per formed before treatment to image the targeted body part. Using these images, the tumor and nearby critical structures are identified to develop the optimal treatment plan. For tumors near the diaphragm (e.g., liver or lower lung lobe), 4D CT scans may be used to track respiratory motion. MRI is often recommended for brain, paraspinal, head and neck, prostate cancers, and extremity sarcomas due to its superior soft-tissue contrast. MRI scans are fused with CT for tumor delineation and organ-at-risk contouring, or used alone in MRI-only simulations with synthesized CT for planning and dose calculation. Unlike CT and MRI, PET reveals tumor metabolism and helps define dose-escalation volumes, especially in head and neck cancers.

AI's automated abilities such as precise tumor volume tracking over time, simultaneous monitoring of multiple lesions, linking phenotypic nuances to genotypes, and predicting outcomes via comparisons with vast tumor databases—can enhance clinicians' qualitative judgment. DL methods further improve generalizability across diseases and imaging types, reduce noise sensitivity and errors, and may enable earlier treatments and significant clinical advances. While most studies remain preclinical, the evolution of automated radiographic "radiomic" markers may ultimately shift cancer diagnostics by identifying actionable tumor abnormalities.

Today's digital pathology faces three core challenges that must be addressed as digitization expands, and AI capabilities evolve, these include:

(1) Improved efficiency, quality control, and image management in laboratory operations;

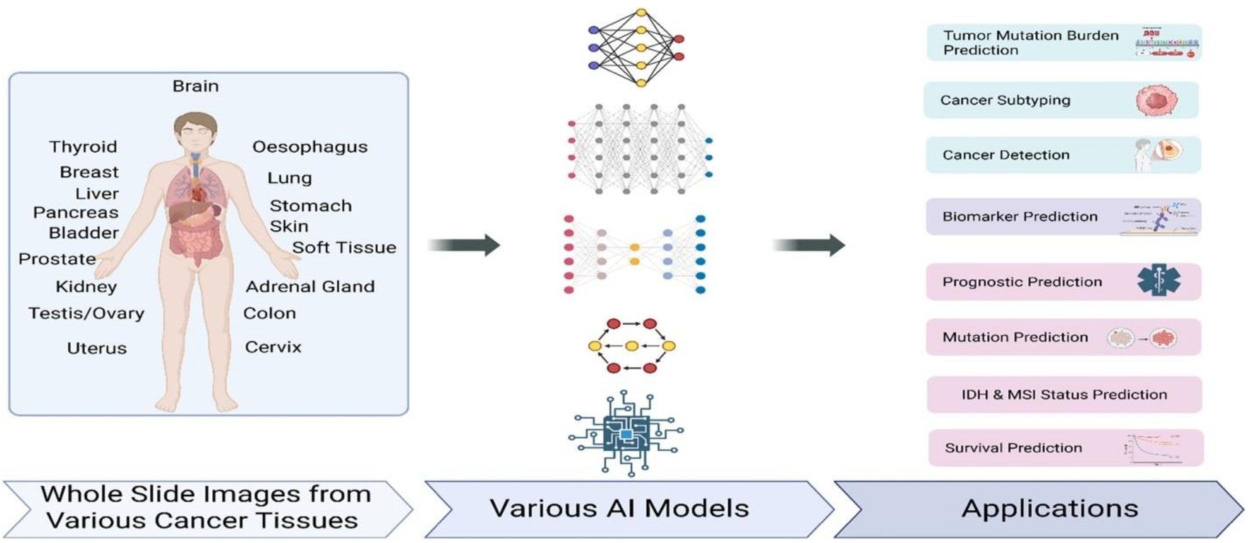
(2) Clinical decision support, where algorithms are used to identify areas of interest or make specific diagnoses; and

(3) Research and development, where new biomarkers, transcriptomics , and correlations between image characteristics and prognostics have been discovered.

The application of AI for digital pathology predates the introduction of whole-slide images (WSIs). Previous research showed that computer vision and AI methods can distinguish between diseases in pathology images. However, previously chosen regions of interest (ROIs) made up the majority of those image datasets. Because pathologists must first choose the areas of interest, this approach is extremely time-consuming and technically impractical to integrate into a laboratory's clinical process. One major obstacle in healthcare systems is the early-stage identification of cancer, mainly because early stages of cancer are modest and frequently asymptomatic. Early cancer detection is essential for effective treatment and higher survival rates, but there are a number of reasons that make this process complex and challenging. This investigation explores the complexities of these problems, including systemic, technological, and biological ones, and emphasizes how urgently diagnostic methodology innovations are needed.

Alternative AI models such as AI Initiatives at the University of Pittsburgh assist pathologists in diagnosing prostate cancer, and the University of Pittsburgh Medical Center (UPMC) has used AI technologies such as Galen Prostate™ from Ibex Medical Analytics. In order to detect cancer and evaluate characteristics like Gleason grades,per neural invasion, and tumor sizing. Galen Prostate uses DL algorithms that have been trained on large datasets, including rare prostatic cancers. North well Health created INav, an AI-powered diagnostic tool, to improve pancreatic cancer early diagnosis and treatment [74]. iNav detects patients with radiographic signs of pancreatic cancer through radiology data analysis, enabling timely care. It uses an NLP classifier trained to recognize phrases in radiology reports linked to pancreatic cancer, scanning for language patterns and keywords tied to masses or lesions. When indicators appear, iNav flags them for further medical review. Given pancreatic cancer's late detection and poor prognosis, iNav improves early detection by proactively analyzing imaging. It cut the diagnosis-to-treatment time by 50%, tripled biospecimen study participation, and increased referrals to multidisciplinary clinics, improving care and research opportunities. An improved DL model called Dual-Domain Residual-based Optimization Network (DRONE) was developed. DRONE reduces artifacts and boosts image quality by integrating image and data domains (sinogram). It has three modules: the embedding module expands sparse sinogram data via an encoder-decoder network, enriching inputs; the refinement module improves initial images using a deep CNN; and the awareness module ensures consistency between sinogram and reconstructed images through regularization, integrating outputs from the other two modules. DRONE addresses sparse-view CT challenges by combining outputs across modules. Its performance evaluated using PSNR, SSIM, and RMSE surpassed conventional and other DL methods in reconstruction accuracy, feature retention, and edge clarity. The integration of AI and ML into cancer diagnostics has markedly improved accuracy, speed, and treatment personalization. AI excels at analyzing complex datasets, leading to more accurate diagnoses and faster treatment initiation, which improves outcomes. It also supports personalized medicine by integrating genetic and clinical data to tailor treatments. Developing AI/ML models for cancer detection involves key steps. Data collection requires diverse, high-quality datasets, including imaging, genomics, and patient histories. Preprocessing ensures data consistency via normalization, augmentation, and annotation. Model selection is task-specific CNNs for images, RNNs or LSTMs for sequential data, and decision trees for classification. Models are trained on large datasets and validated regularly to enhance accuracy. CNNs effectively analyze images like MRIs and mammograms; LSTMs and RNNs process sequential clinical data; decision trees and RFs support diagnostic decision-making. These models have demonstrated strong performance in cancer detection.

FIGURE-3: **Whole slide images from different cancer tissues are processed using diverse AI models to enable key applications like cancer detection, sub typing, mutation and biomarker prediction, prognostic evaluation, and survival forecasting, advancing precision oncology through deep learning insights.**



3.6 AI in treatment planning and decision support

The use of AI to resolve medical problems has long been hailed as a disruptive and near-future development. It has a lengthy history that began in the 1970s when clinical decision support systems (CDSSs) needed human input to choose qualities for these expert systems and supply rules for decision-tree approaches. CDSSs based on AI emerged with the technical assistance of big data and ML. CDSSs assess drug efficacy, product accessibility, adverse reactions, patient financial status, and medical insurance types by combining various medical records, literature, and clinical research data. They then offer tailored recommendations to assist clinicians in optimizing treatment plans. AI's uses have grown beyond everyday problem solving to include medical professional domains like pathology diagnosis, image diagnosis, clinical treatment decision-making, prognosis analysis, and new drug screening.

CDSSs based on AI technology have not fully achieved human–computer interactions in clinical practice as image-aided diagnosis systems because the ethics of applying AI as an emerging technology in clinical decision-making have not been thoroughly established. The Chinese Society of Clinical Oncology-Artificial Intelligence (CSCO AI), Watson for Oncology (WFO), and other organizations are now using and promoting CDSSs globally.

As the first commonly used CDSS in the field of cancer, WO progressively gained global recognition in the areas of gynecological, lung, colon, rectal, breast, and stomach cancers. Medical personnel just need to enter a case's structured data according to the WFO system. The technology will produce extremely consistent evidence and the most conventional treatment strategy for the particular situation in less than a minute.

AI-based CDSSs simulate human reasoning to support clinical decisions, using ML models like DL, SVMs, LR, and ANNs. Built on structured medical data, they reduce errors, response times, and reliance on memory, enhancing safety, quality, and treatment efficacy.

Different from WFO, the CSCO AI system was established under the CSCO platform using the CSCO data base and guidelines. The CSCO AI system mainly builds different knowledge maps based on schemes in CSCO guidelines. When doctors search for relevant information, it locates the knowledge map and outputs results according to key information. Similarly, it is also updated in real time with guidelines to ensure the timeliness of the system.

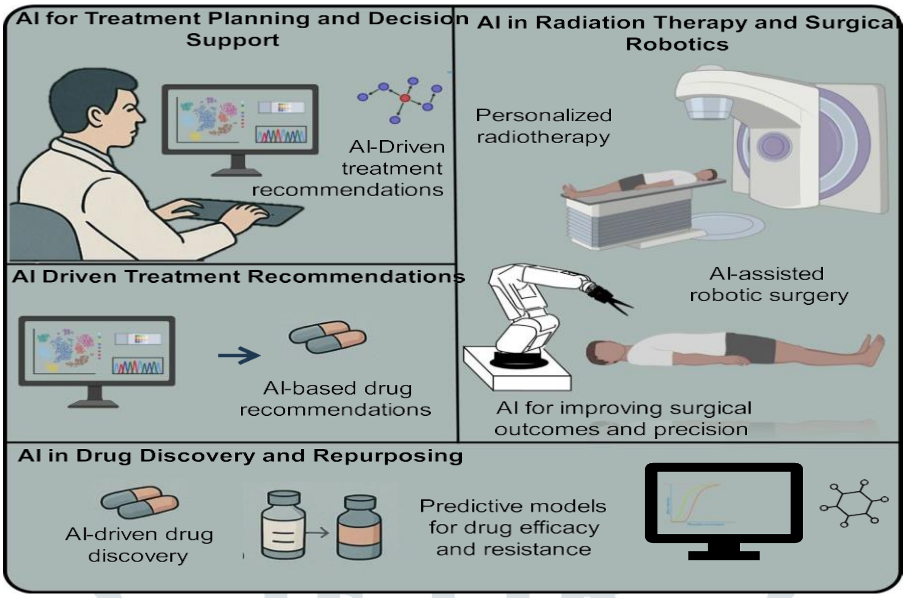
Tempus is transforming precision oncology through AI and ML-powered individualized therapy recommendations. By integrating imaging, clinical records, genomic data, and patient histories. Tempus applies ML and DL (e.g., CNNs) to clinical and genomic data—including a 100,000-patient database to identify cancer drivers and predict treatment response. It supports personalized therapy, though challenges like data quality, bias, and limited diversity remain [174]. Additionally, model interpretability is an ongoing concern, as clinicians require transparent, actionable outputs to guide patient care decisions.

Flach et al. (2025), explored the integration of Paige Prostate Detect, an AI-assisted tool, into the clinical workflow for prostate cancer (PC) diagnosis. The study aimed to evaluate how AI can improve diagnostic accuracy and efficiency during prostate biopsies. Using deep learning models, including CNNs, Paige Prostate Detect analyzes biopsy slides to identify malignant regions and assist pathologists in detecting areas needing further review.

The system was trained on thousands of annotated biopsy samples. Enabling it to assess Gleason scores and distinguish benign from malignant tissues. Preliminary results suggest that AI support may enhance diagnostic speed and accuracy, particularly for less experienced pathologists or challenging cases. However, concerns remain regarding data variability, model interpretability, and the need for large, diverse datasets to ensure generalizability. Importantly, human oversight remains critical to confirm AI-assisted diagnoses.

AI in Cancer Treatment and Therapy Optimization

Figure-4 : **AI applications across cancer care workflows from treatment planning and drug recommendation to robotic surgery and drug discovery.AI enhances decision support, enables personalized radiotherapy, assists in surgery, and predicts drug efficacy and resistance, thereby improving precision, outcomes, and therapy development.**



4. CONCLUSION

AI is no longer a secondary adjunct in oncology—it is becoming an essential, intrinsic component in advancing cancer therapeutics. By seamlessly integrating heterogeneous biomedical datasets into clinically actionable insights, AI is transforming every stage of cancer care: detection, diagnosis, treatment, follow-up, and research. T his review underscores both the vast promise and complexity of embedding AI into oncology, spanning imaging modalities (CT, MRI, PET, ultrasound), histopathology, genomics, proteomics, and more. AI shifts clinical decision-making from subjective estimations to high-accuracy, algorithmic diagnostics that often outperform conventional methods in speed, reproduc ibility, and precision. Beyond diagnosis, AI enables personalized treatment planning, fine-tuned radiation dosing, enhanced robot-assisted surgeries, and discovery of novel therapeutic targets via data-intensive drug development pipelines. On the patient management front, AI-powered wearable and virtual assistants facilitate real-time remote monitoring, boost treatment adherence, and detect complications early. In clinical research, AI optimizes study design, patient stratification, and recruitment through real-time eligibility checks. Yet despite these advancements, challenges remain in achieving universal clinical adoption. Concerns about algorithm transparency, reproducibility, and interpretability underscore the need to build trust among providers and patients. Regulatory frameworks for AI in healthcare are still evolving, and comprehensive governance models ensuring safety, efficacy, and innovation are urgently needed. Critical data-related challenges—bias, inequity, security, and interoperability—must be addressed, particularly as biased training data risks exacerbating existing health disparities across demographics and regions. A multidisciplinary ecosystem—uniting AI researchers, oncologists, ethicists, regulators, and patient advocates—is essential to create equitable, transparent, and clinically valuable AI deployment standards. Medical education must evolve to equip future healthcare professionals with the skills to responsibly apply AI in clinical practice. Looking forward, AI's convergence with federated learning, edge computing, digital twins, and quantum ML offers exciting potential for highly granular, scalable, and personalized cancer care.Emerging synergies between AI, synthetic biology, and de novo immunotherapy design point toward truly individualized next-generation treatments. Ultimately, deploying transparent, privacy-preserving, and ethics-focused AI models will foster trusted healthcare systems. AI's true potential lies not just in improving current practices but in reshaping oncology into a predictive, preventive, participatory, and precision-driven discipline. With a human-centered approach and collaborative innovation, AI can usher in a transformative era in cancer care—benefiting all patients through smarter data use, outcome-driven strategies, and inclusive clinical impact.

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