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An Overview Of Artificial Intelligence In An Oncology

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Abstract:

Cancer continues to pose a substantial global burden, prompting relentless efforts to enhance screening, diagnosis, treatment, and survivorship strategies. While remarkable progress has been made in recent decades, the delivery of personalized and data-driven care presents ongoing challenges. Enter artificial intelligence (AI), a burgeoning field within computer science renowned for its predictive and automation capabilities. AI holds the potential to revolutionize the healthcare landscape, particularly in oncology, by bolstering precision and effectiveness. The scope of AI applications in oncology is extensive, encompassing the optimization of cancer research processes, refinement of clinical practices—such as the prognostication of multifaceted parameter-outcome relationships—and the deepening of insights into tumor molecular biology. This comprehensive review navigates the current landscape of AI in oncology, delving into its foundational principles, present-day applications, inherent limitations, and the promising vistas that lie ahead. By examining the interplay of AI and cancer care, this review underscores the transformative potential of AI-driven innovations while acknowledging the intricate roadblocks that must be navigated for its successful integration into mainstream healthcare practices.

Keywords: Cancer, Artificial Intelligence, Oncology, Precision Healthcare, Personalized Medicine, AI Applications, Prognostication, Molecular Biology, Data-driven Care, Healthcare Innovation, Clinical Practice, Cancer Research, Automation, Healthcare Challenges, Future Perspectives.

Introduction:

Cancer, a global scourge, continues to exert a substantial toll on human health and well-being, with its pervasive morbidity and mortality echoing across the globe. The year 2020 bore witness to the diagnosis of an estimated 19.3 million new cancer cases, a statistic projected to escalate in the ensuing decades, predicting a staggering 30.2 million new cases by 2040 [1]. Despite commendable progress in the realms of cancer diagnosis and management, exemplified by a reduction in cancer-related fatalities over the past twenty years, the resounding toll of 10 million cancer-related deaths in 2020 serves as a somber reminder of the work that lies ahead [1]. In response, innovation within healthcare, particularly within the realm of cancer care, remains imperative.

However, the journey towards conquering cancer is riddled with multifaceted challenges. Timely identification of cancer remains an ongoing global struggle, as effective screening initiatives grapple with issues of public engagement, financial resources, and incomplete coverage of high-risk populations [3]. Unsystematic expansion of screening programs, lacking evidence-based direction, risks not only straining financial resources but also squandering them within healthcare systems that are often resource-constrained [4].

Furthermore, while strides have been made in diversifying cancer treatment options, the benefits of these novel therapies primarily accrue to a fortunate subset of patients. Additionally, the cost-effectiveness of current treatments remains a point of concern, necessitating urgent efforts to democratize access to cutting-edge treatments and optimize their economic feasibility [4].

The development of new anticancer treatments is an arduous process characterized by extensive time and resource investments. Even when a potential drug navigates the complex landscape of preclinical testing and rigorous clinical trials, the success rate remains disappointingly low, and the challenge of patient recruitment looms large [5]. Remarkably, despite these obstacles, the year 2020 bore witness to the approval or expansion of indications for 64 interventions dedicated to cancer diagnosis and treatment by the US FDA [6]. Yet, the rapid cadence of oncological research inundates physicians with an abundance of pertinent literature, complicating their task of integrating the latest recommendations into their clinical practice.

The intricate data ecosystem originating from oncology practitioners and healthcare systems further amplifies the complexity. Varying from textual notes by physicians to laboratory results, histopathological assessments, intricate medical images, and even patient-generated health data, this data landscape is characterized by its sheer unpredictability. The transformative potential of this data lies dormant without the ability to extract, process, analyze, interpret, and integrate it meaningfully.

Against the backdrop of human cognitive limitations in processing vast and intricate modern healthcare data, the necessity for innovative strategies has become more pronounced. The surge in computational capacity, coupled with the burgeoning availability of storage, has propelled the rise of data processing paradigms like machine learning (ML) and artificial intelligence (AI), offering a formidable arsenal for tackling the intricacies of cancer care. An increasing body of research underscores AI's capacity to personalize cancer care by meticulously sifting through available data. Recent records highlight a surge of 97 registered clinical trials involving AI in cancer diagnosis, with a majority commencing post-2017 [7].

In the pages that follow, we embark on a comprehensive exploration of artificial intelligence's burgeoning role within the oncological landscape. We delve into contemporary AI applications, unveil promising vistas for the future, and candidly address the existing limitations, offering an encompassing view of AI's transformative potential in reshaping the landscape of cancer care.

Artificial intelligence:

Artificial Intelligence (AI) can be defined as a branch of computer science dedicated to emulating intelligent behavior in computers. It operates by utilizing predefined algorithms set by humans or acquired through machine learning to facilitate decision-making and perform specific tasks [8]. Within this AI realm lies Machine Learning (ML), a subset that enables computers to enhance their performance by continuously integrating newly generated data into an existing iterative model [9]. Deep Learning (DL), in turn, is a subset of ML that employs intricate mathematical algorithms through multi-layered computational units, mirroring aspects of human cognition. This encompasses various neural network architectures, such as Recurrent Neural Networks, Convolutional Neural Networks, and Long-Term Short Memory.

Artificial Neural Networks manifest diverse architectures in their application of mathematical principles to data. Their utility shines particularly in analyzing unstructured data [10], a prevalent type of medical information that captures qualitative and subjective details, often derived from patient-provider interactions or imaging procedures. The application of AI to unstructured text data employs Natural Language Processing (NLP) techniques, frequently employing Recurrent Neural Networks, while Convolutional Neural Networks emerge as the frontrunners in harnessing imaging data.

The evolution and validation of ML models entail a sequence of crucial stages, commencing with accurate problem formulation, followed by data collection, pre-processing (including anonymization), model training, internal validation, testing, optimization, evaluation, and ultimate external validation [11]. Each of these steps plays a pivotal role in constructing a robust machine learning model fit for clinical application. Once deployed, continuous monitoring is imperative to detect any performance deviation or drift, thus ensuring model reliability

(Figure 1). Furthermore, the practicality of ML models must undergo assessment through prospective clinical trials, utilizing specialized metrics tailored to each unique problem. A ubiquitous metric in medical classification tasks is the Receiver Operating Characteristic (ROC) curve, which plots true positive rate against false positive rate. The Area Under the ROC Curve (AUROC) quantifies accuracy. Additionally, the Confusion Matrix enters the fray to gauge sensitivity, specificity, and precision.

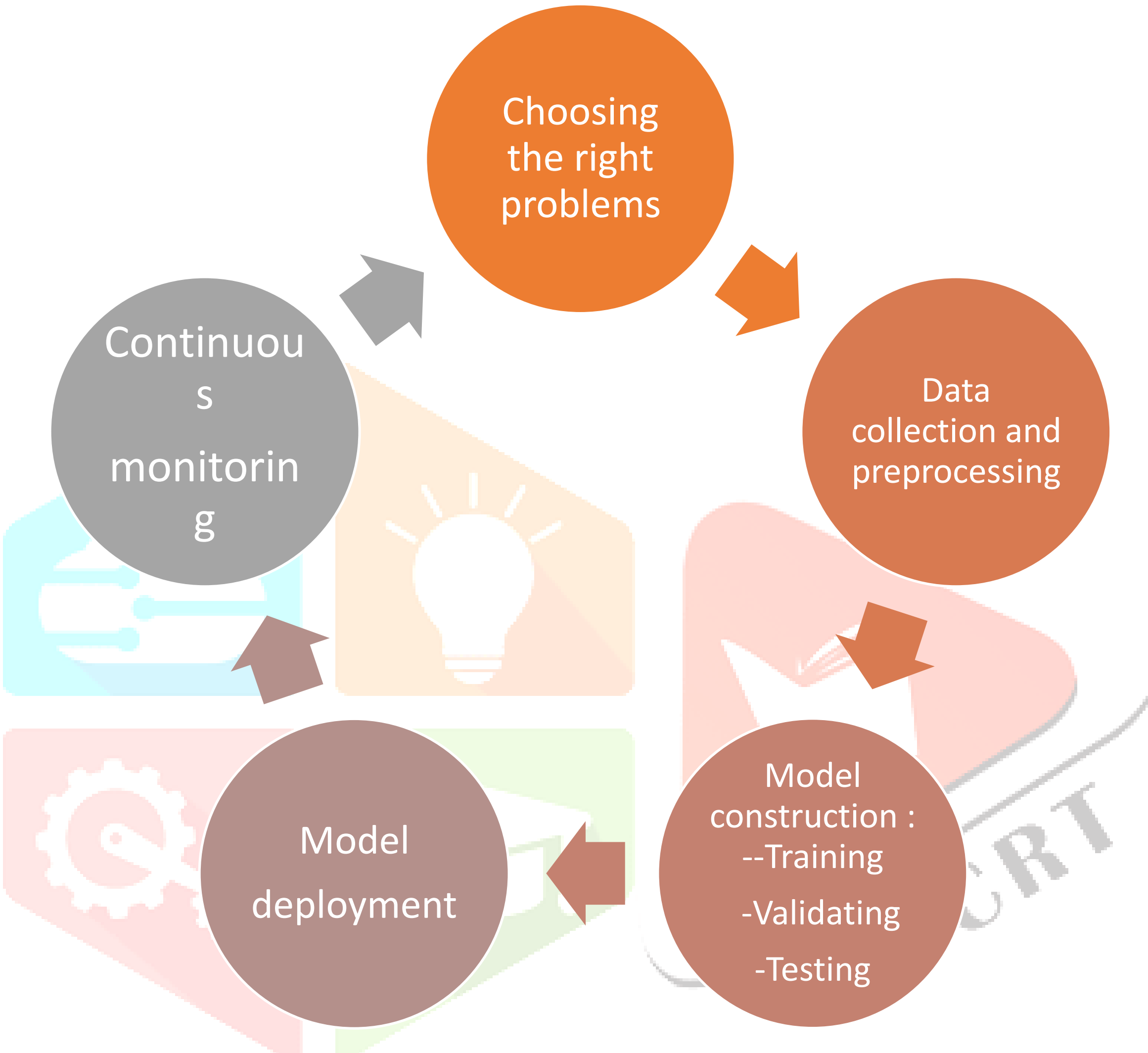

Figure 1. Artificial intelligence flywheel.

Graphic representation of the artificial intelligence and data cycle for building effective and responsible machine learning models for healthcare.

Artificial intelligence and precision oncology glossary:

Terms Definitions

Algorithm: A set of rules for solving a problem or for performing a task

Area under curve: A measure of a classifier's accuracy for a binary classification

Artificial intelligence Systems that display intelligent behavior by analyzing their environment and taking actions – with some degree of autonomy – to achieve specific goals.

Artificial neural network: A computational model in machine learning, which is inspired by the biological structures and functions of the human brain

Computer-aided detection/diagnosis: Systems that use computer science to assist doctors in the interpretation of medical images

Deep learning: A subfield of machine learning that mimics the capacity of the human brain to perform unsupervised learning tasks using multiple layers of neural networks

Machine learning: A field in computer science that builds computational models that have the ability of 'learning' from data and providing predictions

Radiomics: A method that extracts and analyses large amounts of advanced quantitative image features with the intent of creating mineable databases from radiological images

Radio genomics: A field that studies the correlation between cancer imaging features and gene expression

Artificial Intelligence in Cancer Imaging:

The integration of artificial intelligence (AI) holds particular promise in medical domains that heavily rely on image analysis, most notably radiology and pathology [14]. Within radiology, AI, and specifically Deep Learning (DL) algorithms, finds diverse applications in the realm of cancer care, encompassing disease classification, detection, segmentation, characterization, and ongoing monitoring [15, 16].

Classification: AI is pivotal in enhancing the outcomes of cancer screening initiatives. By aiding radiologists, AI not only accelerates diagnostic processes but also supports the classification of minute lesions. This technology contributes to optimizing workflow, facilitating prioritization, and even leading to significant enhancements in mammography-based breast cancer screening through the amalgamation of AI and human expertise [17, 18].

Detection: AI plays a vital role in identifying cancerous lesions that might elude human perception. It operates effectively in tasks like identifying lung nodules [19] or pinpointing brain metastases in MRI scans [20]. This process hinges on the utilization of bounding boxes to delineate the lesions or objects of interest, thereby aiding physicians in their image interpretation, such as detecting lung nodules [21].

Segmentation: AI-driven segmentation empowers the precise classification of individual pixels, distinguishing organs or lesions. This granularity extends to evaluating volume and size, as observed in scenarios like quantifying brain gliomas for management, risk assessment, and prognostication purposes [22].

Characterization: Leveraging deep learning methodologies, AI extracts a multitude of features that evade human observation from medical images. This capacity holds immense potential for discerning disease patterns and characteristics. The burgeoning field of radiomics explores these features, progressively intertwining them with clinic genomic insights. The fusion of radiomics and AI informs models capable of accurately predicting treatment responses and potential side effects [23]. This approach proves adaptable across various cancer types like liver, brain, and lung tumors [24, 25]. Notably, AI utilizing radiomic features extracted from brain MRI exhibits proficiency akin to trained neuroradiologists in distinguishing between brain gliomas and metastases [26].

Monitoring: The capabilities of AI extend to monitoring lesions, tracking stability versus progression. AI's ability to discern an array of discriminative features within images inaccessible to human perception can profoundly transform cancer monitoring paradigms [15].

Generative Adversarial Networks (GANs) constitute a class of AI models designed to produce novel images from diverse datasets. A potential utility of GANs involves generating synthetic Computed Tomography (CT) images from Magnetic Resonance Imaging (MRI) data, presenting a prospect to bolster radiotherapy planning [27]. Moreover, their efficacy extends to automating dose distribution for Intensity Modulated Radiation Therapy (IMRT) in prostate cancer cases [28].

Expanding this domain, generative networks encompassing varied architectures such as Autoencoders (AEs) and Variational Autoencoders (VAEs) exhibit the ability to enhance the acquisition of multimodal images like MRI and CT scans. This augmentation holds promise in mitigating radiation exposure and intravenous contrast utilization [29–31]. Given the routine scans essential for oncology patients, the incorporation of AE and VAE has the potential to curtail healthcare expenses while elevating patient safety.

In parallel, deep learning models find application in prognosticating the future onset of cancer. This aligns with the concept of a "care gap," where routine scans or MRIs for unrelated conditions offer an opportunity for AI models to predict diseases. For instance, some AI models have been developed to forecast cardiovascular scores based on CT scans [32, 33]. A notable study demonstrated the capability to predict a 5-year breast cancer risk from ordinary mammograms through deep-learning Convolutional Neural Networks (CNNs) [34]. This ability to prognosticate cancer from normal scans holds substantial potential for a wide-ranging societal impact.

AI's reach also extends to domains like pathology and medical images. Golatkar *et al*. showcased a deep learning model grounded in Convolutional Neural Networks, boasting over 90% accuracy in distinguishing between benign and malignant histology using Hematoxylin and Eosin (H&E) stained breast biopsy samples [35]. Dermoscopic images have similarly been harnessed for classifying lesions as benign or malignant, rivaling the accuracy of trained dermatologists [36].

Presently, select AI applications are already finding their way into clinical practice [37–39]. However, continued development, fine-tuning, and real-world application of AI necessitate a trained workforce. This underscores the urgency in equipping the next generation of physician-scientists with the requisite knowledge of AI and its interplay with oncology [40].

Artificial intelligence for predicting clinically relevant parameters:

The exploration of the extensive data encompassed within Electronic Health Records (EHRs) has opened avenues for researchers to unearth patterns pertaining to clinically significant parameters. This involves discerning trends both at an individual level and over time, leveraging the amalgamation of individual data with historical data that has been aggregated [41]. EHRs inherently structure data in a standardized format, thereby enabling the application of AI-driven natural language processing algorithms. These algorithms emerge as a cost-effective and straightforward means to underpin medical decision-making processes. A concrete instance is the concept of "deep patient representation," wherein patient data harvested from expansive EHR databases is harnessed through an automated mechanism to prognosticate desired outcomes [41]. In this paradigm, the raw information stored in EHRs undergoes intricate processing via multiple neural network layers, culminating in clinically relevant analyses like the prediction of disease development risks [41]. However, translating the applicability of such models to real-world scenarios necessitates surmounting challenges encompassing data standardization, technological infrastructure, and fostering an organizational culture that values data integration and utilization.

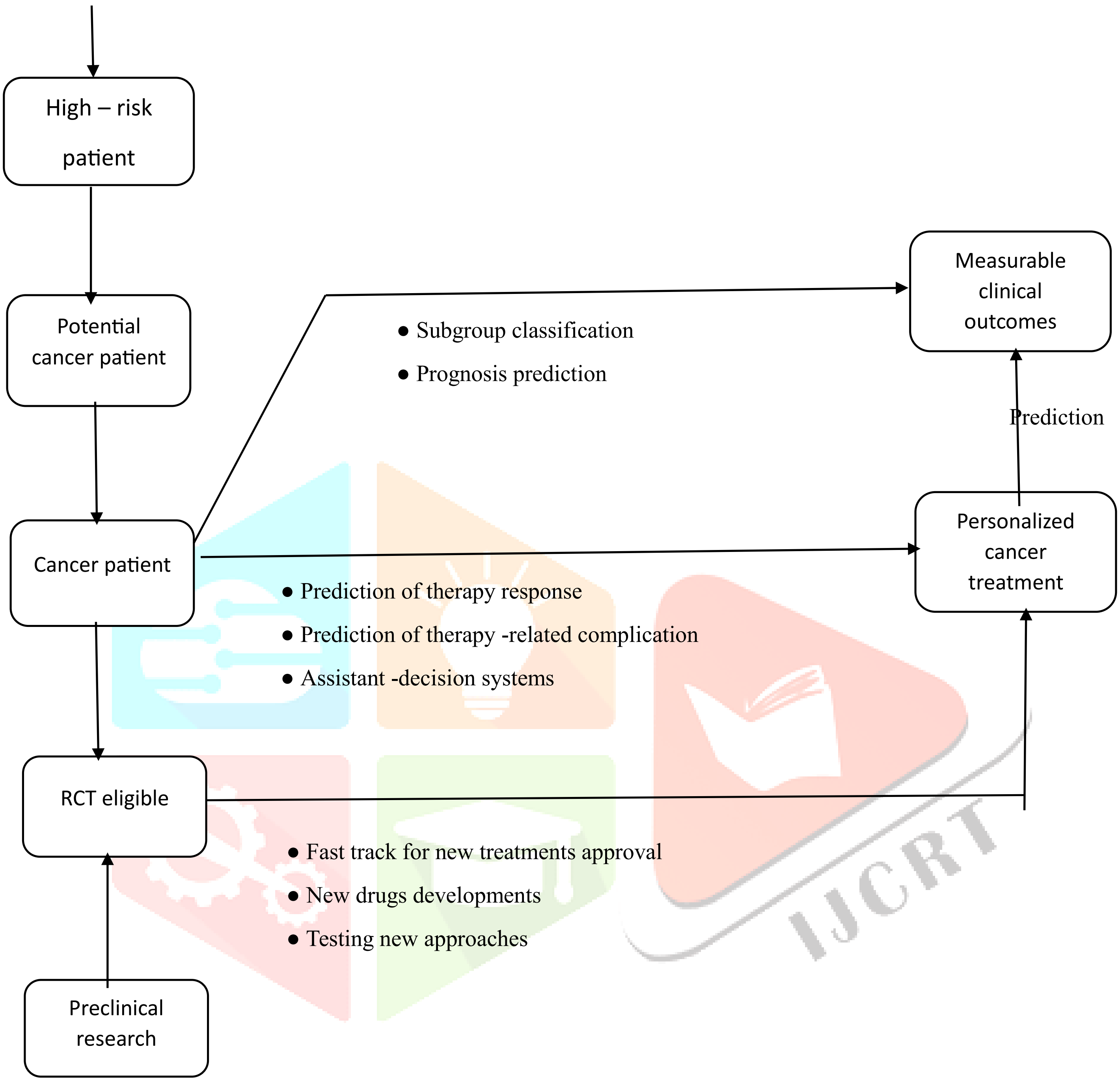

Figure 2 illustrates the prospective domains where artificial intelligence (AI) can exert its influence throughout a cancer patient's journey. AI-driven models find utility not only in preclinical phases (depicted in the orange box) but also extend their impact to clinical scenarios, spanning both pre-diagnosis (green box) and post-diagnosis (blue box) stages. Within the realm of real-world oncology care, AI's potential unfolds across multiple facets, including the optimization of risk assessment, screening recommendations, diagnostics, prognostics, decision-making processes, and even the anticipation of treatment-related outcomes. Furthermore, AI holds the capability to bridge the chasm between clinical research and routine oncological practice by streamlining activities such as drug repurposing, expediting the discovery of novel treatment approaches, and enhancing the precision of patient selection for participation in Randomized Controlled Trials (RCTs). This amalgamation of AI-driven advancements into the oncological landscape holds promise for enhancing patient care and research endeavors.

Medical imaging serves as a valuable reservoir of prognostic insights. The realm of Radiomics offers a potent avenue for evaluating and forecasting clinically pertinent factors within the field of oncology [42]. Given the routine nature of imaging procedures in cancer diagnosis and patient monitoring, the integration of Radiomics into cancer care holds the promise of seamless incorporation. Notably, other data modalities like genomic information can also be harnessed for prognostic endeavors [43].

The scope of prognostic parameters that can be assessed and predicted using AI algorithms encompasses risk stratification, treatment complications, survival rates, and therapeutic response, as depicted in Figure 2. Nevertheless, despite the promising potential, there exists a substantial journey ahead, and an integral aspect of achieving success lies in the comprehensive education of all stakeholders involved.

Risk Stratification:

An established application of Electronic Health Record (EHR) data lies in disease risk stratification. Traditionally, the calculation of risk stratification was constrained by the volume of data that could be retrospectively reviewed and analyzed using conventional statistical methods. However, the advent of artificial intelligence-based algorithms has revolutionized this landscape by effectively processing unstructured data and accurately predicting the likelihood of patients developing various diseases, including cancer [41]. Agnostic AI models further refine risk stratification definitions, exerting a tangible impact on cancer screening recommendations [44–49] with commendable precision. A notable instance entails an artificial neural network model designed for colorectal cancer risk stratification, which showcased enhanced accuracy when juxtaposed with prevailing screening guidelines. This was achieved by markedly curbing false positives from 53% to 6% and false negatives from 35% to 5% [45].

The scope of these AI models extends to a population-wide application. Individuals at high risk of cancer, not encompassed by existing screening guidelines yet still susceptible to cancer development, could potentially be identified, enabling early assessment. Consider early-onset sporadic colorectal cancer: it faces limitations in traditional screening methods but could greatly benefit from intensive risk-based screening suggestions [45]. Similarly, individuals assessed as low risk for cancer in spite of current screening recommendations could opt out of screening, thereby affecting the system's opportunity cost [50]. This not only empowers shared doctor-patient decision-making but also alleviates the healthcare system from inefficient and potentially harmful interventions.

In cases where tumors lack established screening protocols and often manifest asymptomatic early stages, personalized risk prediction facilitated by artificial neural network models could facilitate timely diagnosis, conceivably leading to higher cure rates. A prime example is the artificial neural network model designed for pancreatic cancer risk prediction, achieving a commendable Area Under the Receiver Operating Characteristic Curve (AUROC) value of 85% [47]. Such personalized risk-calculating algorithms prove invaluable in prioritizing screening efforts for high-risk individuals, especially within resource-constrained environments.

Treatment Complications:

Artificial Intelligence (AI) stands poised to forecast treatment-induced complications arising from both radiation therapy [51] and chemotherapy [52, 53]. This predictive potential holds the promise of informing comprehensive discussions surrounding the trade-offs between distinct treatment modalities, fostering personalized radiotherapy (RT) dose delivery strategies.

Machine Learning (ML) models have demonstrated the capacity to anticipate emergency room visits and hospital admissions triggered by symptoms linked to cancer therapies [54]. The integration of these forecasts into clinical practice offers a proactive supportive approach to patients at elevated risk. This approach not only elevates patient care but also alleviates healthcare systems by mitigating the burden of avoidable hospitalizations.

Survival & Disease Recurrence:

The realm of survival prediction algorithms has been extended across diverse cancer types such as breast, prostate, and lung cancers [55–58]. Remarkably, AI-driven algorithms exhibit superior predictive accuracy in comparison to conventional analytic methodologies [58]. This efficacy might stem from their enhanced aptitude for handling variables characterized by nonlinear relationships, rendering them more relevant in real-world contexts. The prognostication of cancer survival assumes significance in tailoring treatment approaches. High-risk patients can receive reinforced treatment planning, while interventions offering marginal benefits to low-risk patients could be circumvented [55]. Furthermore, the utilization of AI models proves instrumental in gauging the risk of disease recurrence post curative treatments. In this capacity, AI's accuracy surpasses that of traditional statistical models [59], paving the way for refined optimization of clinical follow-up plans.

Therapy Response:

Artificial Intelligence (AI) holds the capability to forecast treatment response by leveraging tumor characteristics gleaned from radiological images [60–62]. This predictive prowess is particularly applicable in gauging individual patient reactions to high-cost treatments, including the likes of immunotherapy [61]. Such predictive insights not only influence patient care decision-making but also streamline the judicious allocation of healthcare resources. Additionally, AI-driven models facilitate the anticipation of complete pathological response subsequent to neoadjuvant treatments [62]. This prediction assumes significance as it enables the identification of patients suitable for a conservative approach, potentially mitigating the necessity for radical interventions. Furthermore, algorithms incorporating pharmacogenomics have been devised to prognosticate individualized treatment responses [43].

Artificial Intelligence in Cancer Diagnosis:

The realm of cancer diagnosis is also ripe for optimization through the integration of Artificial Intelligence (AI). A striking example lies in AI-powered colonoscopy, where its adeptness in efficiently identifying benign polyps renders resection unnecessary, thereby yielding a cost-effective intervention [63]. This not only conserves healthcare resources but also averts adverse events associated with more invasive treatment methodologies. Ensuring precise diagnosis of cancerous and precancerous lesions offers the potential to curtail overtreatment. Illustratively, AI algorithms bolstering the evaluation of coloscopic images exhibit remarkable accuracy in predicting precancerous lesions during cervical cancer screening [64]. By enabling accurate cancer stratification at diagnosis, AI contributes to minimizing invasive interventions and the need for unwarranted surgical procedures [65].

An additional facet of AI's diagnostic prowess involves the identification of molecular features sans the need for high-cost genetic testing. Notably, AI-driven algorithms demonstrate efficacy in predicting microsatellite instability through the analysis of common Hematoxylin and Eosin (H&E) stained tissue slides [66, 67]. This approach of low-cost and comprehensive biomarker analysis holds potential in supporting the targeted application of immunotherapy in specific cases and facilitating the identification of high-risk familial instances.

Artificial Intelligence in Cancer Research:

Recent investigations underscore that the advantages of utilizing Artificial Intelligence (AI) extend beyond the optimization of established treatment strategies within cancer care. AI's applicability extends to preclinical domains encompassing basic and translational research as well as the development of cancer drugs [68]. This is particularly evident in AI's role in assimilating and processing data from diverse databases, thereby facilitating drug repurposing [69]. By swiftly identifying potential novel drugs at a cost-effective rate, AI streamlines drug discovery processes [69]. Furthermore, AI-driven drug testing simulations offer the capability to predict the efficacy of cancer therapies, subsequently enriching outcomes in in vivo experiments [70] and thereby expediting the trajectory of clinical research.

The incorporation of AI also augments the efficiency of clinical trials. AI models can predict study outcomes, thus potentially reducing the costs associated with drug development [71]. Additionally, AI has demonstrated its utility in identifying suitable participants for clinical trials [72]. By incorporating inclusion and exclusion criteria and conducting searches within Electronic Health Records (EHRs), AI expedites participant recruitment. These AI-driven systems exhibit remarkable accuracy while necessitating only a fraction of the time compared to manual reviews [73]. Previously documented data highlights that a heightened rate of clinical trial enrollment not only expedites advancements in cancer treatment but is also correlated with improved survival outcomes within the cancer population [74].

Artificial Intelligence and Personalized Medicine:

Numerous strides within oncology patient care have been propelled by the abundance of information extracted from patients' distinct biological and clinical attributes, encompassing genomics, radiomics, metabolomics, and various other "-omics" dimensions. Coupled with the advancement of biomarkers, targeted therapies, imaging techniques, and wireless monitoring devices, this wealth of data has paved the way for the emergence of Artificial Intelligence (AI) as a pivotal tool for physicians striving to deliver precise and accurate care [75]. AI's capacity for extensive data analysis generates recommendations that prove instrumental in the realm of personalized medicine. Several key processes stand to benefit significantly from AI's impact, including cancer prevention, drug discovery, and interventions grounded in genomics [76].

In the domain of molecular biology, AI functions as a catalyst for unique insights and enhancements in comprehending tumor biology. The interdisciplinary collaboration between biological and computer scientists is forging novel pathways in this arena [77]. Given that cancer is fundamentally a disease of the genome, it is unsurprising that oncology has reaped notable rewards from AI-driven innovations. For instance, AI-assisted DNA methylation assessment in cancers has demonstrated its utility in classification and prognostication [78]. Employing machine-derived DNA methylation approaches can result in the reclassification of over 70% of tumors previously labeled by human experts, potentially leading to significantly divergent prognostications and treatment decisions [79].

A seminal study by Capper et al. showcased the prowess of AI in tumor classification, where whole-genome methylation analysis using Illumina's HumanMethylation450 (450 k) or Methylation EPIC (850 k) array platforms exhibited 93% accuracy in classifying 82 classes of brain tumors. This accuracy notably surpassed that achieved by pathologists [80].

AI-powered decision support systems, exemplified by Watson for Oncology, have demonstrated commendable concordance with decisions rendered by multidisciplinary teams. This affords expedited and resource-efficient patient-level decision-making [81]. Additionally, novel algorithms capable of predicting waiting times for cancer surgeries empower a personalized pre-rehabilitation approach [82], potentially culminating in improved surgical outcomes.

While AI systems offer precise data and image analyses, the utility of their results hinges upon their validation, interpretability, and clinical relevance. The successful integration of AI-based systems into clinical practice necessitates the training of end-users and a fundamental grasp of the methods by all stakeholders, encompassing their limitations and ethical quandaries [83, 84]. AI models also hold promise in intricate scenarios, such as patients presenting with cancer of unknown primary, which constitutes 1-2% of newly diagnosed cancers. Notably, a deep learning model founded on H&E-stained whole-slide imaging achieved an 83% accuracy in classifying the site of origin for metastatic tumors [86]. These technologies prove especially valuable since most patients lack access to extensive tumor characterization.

AI's role in precision oncology is manifest; it augments human capabilities by facilitating the incorporation of progressively intricate knowledge into clinical decision-making processes. This manifests as the ability to interpret diverse and intricate data and subsequently apply it to personalized patient management.

AI Implementation from Labs to Clinics: Challenges and Prospects:

While AI-driven algorithms have found their footing in data evaluation within various industries, transitioning their utility to clinical practice presents a complex challenge [87]. This transition is met with barriers encompassing limitations in data collection and training, dearth of prospective clinical validation, user education complexities, and adherence to ethical and regulatory guidelines [88, 89]. These challenges span from the accuracy of data range to the relevance of compiled information. The crux lies in acquiring meaningful data that is not only of high quality but also amenable to processing [90].

The initial phase of data analysis entails pre-processing defined sets of data. This involves tasks like normalization, noise filtration, and feature selection, especially when amalgamating multiple datasets. Normalization is pivotal to obviate bias when analyzing distinct datasets that have been merged. Feature selection, another critical step, significantly influences the efficacy of classification, regression, and pattern recognition algorithms. In the realm of precision oncology, a key challenge resides in harmonizing data sourced from diverse omics types and multiple information streams to predict biomarkers or clinical outcomes [90].

Furthermore, the medical community exhibits a relative lack of familiarity with AI, its methodologies, and applications. Comprehensive education spanning patients, providers, and administrative personnel is imperative to effectively harness advancements for the betterment of care quality [40, 83, 91]. The seamless integration of any novel tool into clinical workflows is pivotal for its long-term success. Ethical concerns also come to the fore in the context of AI in healthcare. Striking a balance between leveraging patient data appropriately and respecting privacy regulations while prioritizing patient safety is a paramount consideration [84].

Incorporating AI can yield cost savings across multiple scenarios, as delineated in this review. However, considerable investments in infrastructure are prerequisites for its effective application. Costs associated with data storage, computational power, and human resources, including information technology and bioinformatics professionals, need to be factored in for the consistent and timely utilization of these tools [92]. The advent of cloud services may alleviate some initial investment burden, potentially diminishing the need for institution-specific high-performance computing clusters and dedicated experts. Nevertheless, expenses related to storage and computational time remain significant, and defining reimbursement structures for AI-driven clinical services becomes essential. Implementing stringent quality control processes becomes indispensable to ensure the safe application of this technology [93]. Notably, though the developmental and implementation costs of AI may pose initial challenges, these investments promise substantial process enhancement with minimal additional future expenses [87].

Future Perspectives:

As challenges are confronted and AI algorithms gain validation through prospective studies, the trajectory of AI-based models is poised to integrate seamlessly into every facet of healthcare. In the near future, the applications of AI in oncology are set to be driven by data intelligence, fostering an enhanced comprehension of tumors, facilitating more precise treatment alternatives, and refining decision-making processes [94]. This progression will ultimately usher in an era where oncology becomes an even more precise specialty, centered around the patients' needs and well-being [94].

Furthermore, the integration of risk assessment tools into smartphone applications is anticipated to provide instantaneous cancer risk estimations to the general populace. Individuals receiving high-risk estimations would be incentivized to seek medical attention and adhere to professional recommendations. Simultaneously, risk reduction estimations could motivate individuals to adopt healthier habits, such as smoking cessation or increased physical activity. Within primary care settings, algorithms are poised to guide physicians in determining the optimal moments for patient referrals to high-complexity healthcare centers. The incorporation of algorithms into Electronic Health Record (EHR) systems offers healthcare facilities an avenue to better allocate resources, based on an improved understanding of patient subgroups at elevated risk of cancer development or cancer-related complications. This envisioned future underscores the potential of AI to reshape healthcare in ways that enhance both patient outcomes and resource optimization.

Conclusion:

In conclusion, the influence of AI on healthcare has been substantial and its transformative potential within the medical field is poised to persist. Its applications span across various facets of cancer care, encompassing research, screening, diagnosis, treatment, and monitoring. Beyond these, AI's capacity to mitigate healthcare expenses and address disparities is also noteworthy. A plethora of tools has been devised to harness the multifaceted medical data landscape, incorporating elements like free-text records, laboratory findings, imaging outcomes, radiological images, and omics data. As we look ahead, it becomes evident that further research is imperative to ensure the sustained analytical and clinical validity, as well as the clinical utility of these AI-driven advancements.

Executive summary

• Artificial intelligence (AI) essentials: main concepts about AI are discussed in this part to enable a better comprehension of the article for healthcare workers.

• Artificial intelligence for cancer imaging: current applications of AI in oncology imaging and future perspectives on how it can impact even more healthcare.

• Artificial intelligence for predicting clinically relevant parameters: how AI is enabling better understanding of individual patients, such as risk factors, treatment complications, therapy response and survival.

• Artificial Intelligence for cancer diagnosis: examples of AI-powered tools that are improving cancer diagnosis accuracy.

• Artificial intelligence for cancer research: how AI can reduce costs and time in cancer research such as drug discovery and patient selection for clinical trials.

• Artificial intelligence and personalized medicine: cases whereas AI can improve personalized medicine from molecular and genomics to a more abroad perspective.

• Limitations and future perspectives: a summary from the limitations and future impacts of the previously discussed applications.

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