ijtos 2024; doi 10.22376/ijtos.2024.2.1.37-45

International Journal of Trends on OncoScience

ISSN-2583-8431

Review Article

AI for Oncology Research

Artificial Intelligence in Oncology: Present Potential, Prospective Prospects, And Ethical Reviews

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Abstract: Over the last ten years, Artificial Intelligence (AI) has significantly contributed to solving several health issues, such as cancer. Deep Learning (DL), a subset of adaptable AI that facilitates automated identification of important characteristics, is rapidly used in many fundamental and clinical cancer investigation domains. This review provides a comprehensive overview of recent instances of AI utilized in oncology. It highlights how DL techniques have effectively resolved previously deemed unsolvable issues and discusses the challenges that must be addressed for the wider implementation of such applications. In addition, we emphasize valuable resources and datasets that might facilitate the use of AI in cancer research. In the next decade, the development of novel AI methods and their practical use will provide valuable knowledge in the field of cancer. The advancement of AI technology has proven rapid in recent times and is being incorporated into every facet of life. The medical profession is also advancing in the deployment of AI-equipped medical equipment. AI is anticipated to have a significant impact on achieving the present worldwide movement towards precision medicine. This article offers a comprehensive summary of the historical development of AI and the current advancements in medical AI, with a specific emphasis on cancer.In addition, while AI has significant promise, several unresolved concerns exist.

Keywords: Artificial Intelligence in Oncology, Oncology, Deep Learning, Colorectal Cancer, Breast Cancer, and Histopathology.

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Received On **11 December 2023**
Revised On **21 December 2023**
Accepted On **29 December 2023**
Published On **5 January 2024**

Funding This research did not receive any specific grant from any funding agencies in the public, commercial or not for profit sectors.

Citation Ammar A. Razzak Mahmood, Dr Roopa Murgod, Saswat swarup Badapanda and Dr. John Abraham , Artificial Intelligence in Oncology: Present Potential, Prospective Prospects, And Ethical Reviews.(2024).Int. J. Trends in OncoSci.2(1), 37-45 http://dx.doi.org/10.22376/ijtos.2024.2.1.37-45

1. INTRODUCTION

AI is a study domain that uses computers to imitate human intellect. Machine learning is a specialized area within the science of AI that uses mathematical and statistical techniques to enhance the capabilities of computers. DL is a specific branch of machine learning that is distinguished by using artificial neural networks with several layers. The phrase "DL" encompasses a collection of novel approaches that have shown significant enhancements in performance when compared to the current state-of-the-art machine learning algorithms across several fields[1]. DL has been successfully used to diagnose illnesses by classifying radiological or pathological pictures, achieving performance equivalent to or above that of clinical professionals. Given the considerable anticipation around this technology, it is already being used in pharmaceutical research[2]. Automated algorithms that uncover significant arrangements may deliver practical insights and revolutionize the development of therapies, classification of patients, and study of illnesses. Conversely, AI can violate privacy because of its ability to potentially access personal data, such as genetic sequences, while processing information. Medical professionals and biological scientists must have a fundamental understanding of DL, including its applications and potential limitations, to collaborate effectively with AI researchers and utilizeDL in their developments[3]. This is because DL technology relies on large data sets with proper data annotation. Cancer is the predominant foundation of mortality in industrialized nations, and it is projected that the incidence of cases will continue to rise in aging populations. The rapid advancements in machine learning, particularly DL, coupled with the advancements in statistics infrastructure technologies like the graphics processing unit (GPU) and the availability of public databases, have enabled the utilization of large-scale data known as big data. This has generated significant interest in AI technology worldwide. Presently, AI heavily relies on machine learning as its fundamental technology. Machine learning approaches refer to processes that acquire knowledge from a set of sample data, identify patterns within this data, and use this knowledge to analyze and forecast fresh data. AI is essential in identifying, categorizing, analyzing the tissue characteristics and genetic factors, and detecting molecular markers associated with Colorectal Cancer (CRC) at an early stage[5]. We examine the possibility of AI-based diagnostics and therapies due to the abundance of current screening data and advancements in life anticipated resulting from early identification of breast and colon cancer. Central nervous system (CNS) tumours are few and are associated with a grim prognosis[6].Examining AI in these uncommon tumours may provide insights into the potential for AI integration to enhance the present standard of care. AI and radiomics have significantly improved the recognition rates and streamlined numerous time-consuming processes in assessing glioma grading, pre-intraoperative planning, and postoperative follow-up in CNS tumours[7].

1.1 AI and Deep Learning (DL)

The DL approach originated from examining artificial neurons and was initially introduced in 1943 as a framework for the information-handling neurons in the biological brain[8]. Within a neural network, the input is collected by an initial layer known as the input layer. This layer then communicates its computed value to one or more intermediate layers, referred to as hidden layers, which are interconnected with an output layer. A layer consists of nodes, also known as "units" or "features," connected by edges to the previous and next layers. Each unit modifies the data non-linearly by applying an activation function. A deep neural network often has several hidden layers, perhaps surpassing a count of 100[9]. During the training phase, the network's deeper layers can integrate high-level characteristics from the preceding layer and generate more features of the same kind. Consequently, these algorithms can autonomously generate characteristics suitable for addressing the given goal. DL is a subset of machine learning that has significant potential in the medical domain. DL methods are used in medical applications such as image classification, picture quality enhancement, and segmentation because of their exceptional efficacy in image analysis[10]. DL encompasses a range of methodologies, each suited for different kinds of data. To effectively handle a given dataset, it is crucial to carefully choose the neural network architecture that is most compatible with the data. AI is critically relevant in medical domains involving picture analysis, including radiology and pathology. AI is widely used in radiology, particularly DL algorithms, to analyze imaging data obtained during standard cancer treatment[11]. These applications include many tasks, such as illness categorization, detection, segmentation, characterization, and monitoring. GANs are AI models capable of producing novel visuals by leveraging various input types. One potential use is to create synthetic computed tomography (CT) images using MRI images[12]. This technology can facilitate radiation development. Moreover, it has shown its use in automating the allocation of doses for intensity-modulated radiation treatment (IMRT) in cases of prostate cancer[13]. Furthermore, DL models can forecast the future progression of cancer. The care gap refers to patients getting regular scans or MRIs for unrelated disorders, and several AI models have previously been created to forecast diseases, such as cardiovascular scores derived from CT scans. The research examined the capability of deep-learning Convolutional Neural Networks (CNNs) to forecast the likelihood of developing breast cancer during 5 years based on regular mammograms[14]. The ability to forecast future cancer based on a regular scan has significant potential and is poised to influence the population substantially. Analyzing the extensive data collected by electronic health records (EHRs) has enabled researchers to detect trends in clinically significant variables by examining individual and historical data as aggregated data[15]. EHRs arrange data in a standardized format, allowing AI-powered natural language processing algorithms to analyze data. These may serve as an economical and uncomplicated instrument to facilitate medical decision-making. Radiomics may be used to evaluate and forecast medically significant aspects in the field of cancer[16]. Given the frequent use of imaging for cancer diagnosis and patient monitoring, integrating radiomics into cancer treatment seems feasible. Genomic data may be used for prognostic reasons. AI DL algorithms can assess prognostic indicators such as risk stratification, treatment complications, survival, and therapeutic response.

1.2 AI in The Field of Cancer Diagnostics

Prompt identification of cancer is crucial for preserving the lives of those who are impacted. DL[17] has revolutionizedimage analysis. The widespread use of whole-slide imaging in industrialized nations has led to the amassing of digital pathology pictures, enabling the utilization of DL for pathological diagnosis. A DL system was used to identify cancerous regions in whole slide pictures of radical prostatectomy samples and to repeatedly allocate the Gleason score using a precision of 0.70 (which is 0.28 higher than that of ordinary pathologists). AI may enhance the optimization of cancer diagnosis[18]. Using AI in colonoscopy has shown cost-effectiveness by accurately detecting non-cancerous polyps, eliminating the need for surgical removal. Precise identification of malignant and pre-malignant abnormalities enables the reduction of unnecessary medical interventions[19].Accurate and efficient cancer diagnostics are crucial for early detection and treatment of cancer. AI plays a vital role in improving the accuracy and efficiency of cancer diagnostics. By analyzing vast amounts of patient data, AI algorithms can identify patterns and anomalies that may go unnoticed by human doctors, leading to earlier and more precise diagnoses[20]. This not only saves lives but also reduces healthcare costs by preventing the progression of cancer to advanced stages.Despite the potential benefits of AI in cancer diagnostics, there is a risk of overreliance on machine learning algorithms, leading to false negatives or false positives, which can result in missed diagnoses or unnecessary treatments. Additionally, integrating AI with imaging technologies may introduce technical errors or biases that could affect the accuracy of cancer detection[21].Furthermore, AI systems that assist in the assessment of colposcopic pictures have shown a remarkable level of precision in forecasting the presence of precancerous abnormalities during cervical cancer screening. Utilizing AI technology to accurately categories cancer upon diagnosis may reduce the need for invasive therapies and unneeded surgeries.

1.3 AI in The Field of Cancer Genetics

The clinical assessment of genetic variations relies mostly on scientific and medical literature data. Researchers must locate relevant literature that connects the reported genetic alterations with clinical conditions, efficacious medications, and prognosis data. The use of AI will, thus, become more essential[22]. Before using AI on genomic data, the categorization undergoes a conversion process hooked on a binary table, specifically using one-hot encoding. This table indicates the occurrence or absence of each of the four bases at each place. DL is valuable in cancer genomics for two primary reasons. Furthermore, apart from single-task learning, it facilitates multitask learning, when AI acquires proficiency in numerous distinct tasks concurrently using shared components of a model[23]. Furthermore, it facilitates multimodal learning, a technique for combining diverse forms of data (such as sequence and chromatin accessibility) and using them as inputs. AI autonomously acquires knowledge to integrate various data types effectively during this process. Due to the intricate nature of cancer, it is advisable to include multidimensional data. UtilizingAI, the study of extensive "omics" data (including exome, transcriptome, and epigenome) and patient data about the vulnerability to anticancer treatments in acute myeloid leukaemia led to the discovery of genes associated with drug susceptibility[24]. ExPecto, an additional algorithm, establishes connections between genetic alterations and the prediction of diseases. ExPecto utilizes extensive regulatory areas, including 40-kb promoter-proximal sequences, to forecast the degree of gene expression in each tissue[25]. This framework was constructed using all publicly accessible genome-wide association research and has undergone experimental validation.

1.4 AI in The Context of Breast Cancer

According to the National Cancer Institute Statistics of 2020, Breast Cancer (BC) is the most common kind of cancer[26]. It is a significant contributor to cancer-related deaths, second to lung cancer. The mortality rates of breast cancer in British Columbia have seen a consistent yearly decline from 1989 to 2017, mostly as a result of the progress made in screening techniques and therapeutic interventions[27]. AI has shown significant advancements in the analysis of screening mammograms, the creation of prognostic tools for breast cancer, and the process of creating new drugs. Screening mammography is a commonly conducted screening test associated with significant limitations, including a high prevalence of false positive and false negative results. The use of AI models significantly decreased the amount of effort required. It led to a 69% decrease in false positive results while also improving the sensitivity rate in the screening of mammograms[28]. Various DL algorithms have been examined using different categorization methods to detect mammogram abnormalities. The latest AI model developed by Transpara 1.4.0 screenprint medical BV in Nijmegen, Netherlands, speeds up the process of interpreting mammograms and decreases the amount of labor by 20-50%[29]. This is achieved by removing mammograms with a low probability of malignancy, enabling radiologists to focus on more difficult situations. Radiologists using AI-assisted technologies demonstrated superior area rates under the curve(AUC), sensitivity, and classification ability[30,31].

1.5 AI in The Field of Colorectal Cancer

AI has shown significant achievements in the screening, diagnosing, and treating CRC. AI is revolutionizing colorectal cancer screening and detection via computer-assisted methods for identifying and characterizing adenomas, computer-aided medication delivery strategies, and robotic surgery. Screening has greatly decreased the occurrence of CRC in the last ten years by identifying and restricting the growth of adenomas before they develop into carcinomas. Consequently, there have been suggestions to implement regular screening from 45[32]. The existing methods for screening colorectal cancers (CRCs) encompass invasive techniques such as colonoscopy (considered the most reliable), flexible sigmoidoscopy, and minimally invasive approaches like capsular endoscopy. Additionally, non-invasive procedures like CT colonography or virtual colonoscopy, stool tests for occult blood, faecal immunochemical test, and multitarget stool DNA are employed[33]. Colon-FLag is a programme that uses age, sex, CBC, and demographic information to predict polyps and CRCs. The scores were evaluated against the gold standard colonoscopy and transformed into percentiles. Subsequently, several categories were established, including CRC, high-risk polyps, and benign polyps[34]. Colonoscopy is the preferred invasive testing method for identifying colonic adenoma and CRC. An adenoma is the predominant premalignant lesion. The adenoma detection rate (ADR) quantifies the gastroenterologist's proficiency in identifying adenomas. The adenoma detection rate (ADR) is negatively correlated with the adenoma missing rate and the risk of post-colonoscopy CRC[35]. The AI system, GI Genius, uses green squares to accentuate dubious lesions during a colonoscopy by producing an auditory signal for each marker and presenting it as a video of the endoscope. The finding of using AI to classify CP into malignant and non-cancerous lesions on CT colonography and capsular endoscopy is an intriguing breakthrough. The accuracy of classifying colorectal polyps was greatly enhanced using texture analysis based on the gradient and curvature of high-order images and random forest models in CT colonography differentiation.

1.6 AI in The Field of Endoscopy

AI analysis also focuses on endoscopic pictures as a significant objective. Since Japanese medical equipment makers dominate 99 % of the worldwide endoscope market. Japan is actively engaged in the development of AI for endoscopy[36]. Endoscopy is often recycled for physical examination and stomach and colorectal cancer screening. Additionally, when adenomatous polyps are detected in the colon, they are removed using endoscopic techniques. The pathway from colonoscopy to polypectomy comprises five primary stages they are Identification of lesions, diagnosis including both qualitative and quantitative methods, Medical intervention, Pathological diagnosis, and Monitoring and observation of individuals or activities[37]. Hence, it is essential to identify and not overlook any lesions throughout the inspection meticulously. The endoscopist may readily identify polyps with a projecting morphology, but detecting flat-shaped or similarly colored lesions that blend with the surrounding mucosa requires a certain level of expertise [38]. The colon has several anatomical areas that are not easily visible and necessitate specific procedures to thoroughly examine the inner cavity of the colon, including the spaces between the folds of the mucosal lining. A colonoscopy is a medical procedure involving a technical deficiency on the practitioner's side. In traditional machine learning, the process of extracting the lesion manual identification of characteristics in pictures is performed by humans. Still, with DL, AI automatically develops a diverse range of lesion features[39]. The input pictures are transformed into features via the convolution and pooling layers, and their classification is determined in the output layer. Additionally, the AI autonomously acquires knowledge from the training data using the back-propagation technique.

1.7 AI in The Field of Histopathology

The pathological diagnosis is the ultimate diagnosis of a lesion, which is crucial in deciding the future treatment approach and the usefulness of the therapy. The significance of using AI technology in pathological diagnostics for research and development cannot be overstated. Nevertheless, some issues need resolution, such as the standardization of pathological pictures. This is due to the variations in the techniques used by different institutions for preparing pathological specimens and applying staining procedures. The visual analysis of histomorphology is characterized by a long and unreliable process, typically lacking reproducibility[40]. Advancements in AI have enabled the utilization of deep neural networks (DNNs) for the creation and execution of intricate decision algorithms. DNNs have also demonstrated comparable accuracy to practicing dermatologists in analyzing skin lesions through image analysis[41]. It is anticipated that DNNs will soon be able to conduct more precise analyses using H&E slides, thanks to advancements in high-throughput whole-slide scanning technologies. Consequently, these DNNs function by breaking down pictures into individual pixels and systematically combining them to create shapes and other identifiable features that might serve as diagnostic patterns. Therefore, automated judgments will enhance and refine immunohistochemistry methods, resulting in faster and more economical diagnoses. Using image-based analysis is an economical approach that concurrently decreases the effort required and obviates the need for further confirmatory tests[42]. Training these algorithms extensively with a substantial number of molecular-level verified cases would enhance the ability to identify minor morphological traits that more accurately predict the presence or absence of cancer-related molecular abnormalities. AI-based approaches for detecting, segmenting, diagnosing, and analysis of digitized images Fig 01.

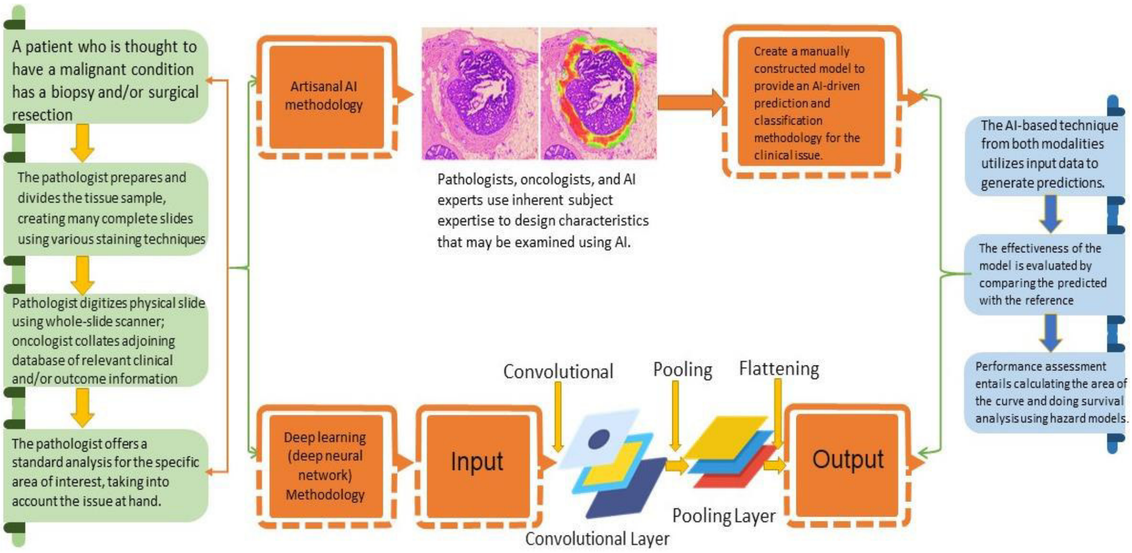

Fig: 01 Methodology and comprehensive structure for AI-based digital pathology techniques.

1.8 AI in The Detection and Diagnosis of Skin Cancer

Melanoma, a kind of skin cancer, is a significant concern in Western nations and is the primary cause of skin cancer-related deaths globally. Melanoma, a highly malignant cancer that arises from melanocytes, resembles benign moles, emphasizing the crucial need to distinguish between the two[43] accurately. Early identification of skin cancer, especially melanoma, is crucial since it not only helps with therapy but also significantly improves the outlook for patients. However, the clinical identification of melanoma may be challenging since it closely resembles other pigmented skin abnormalities such as nevi, seborrheic keratosis, and basal cell carcinoma. AI is a very advantageous tool in the fight against skin cancer[44]. Esteva et al.,'s research revealed that AI's discriminative skills were comparable to those of dermatologists and those without specialized training[45]. Using DL methods like convolutional neural networks, AI was used to categorize and diagnose various skin disorders by analyzing a large library of roughly 130,000 photos of over 2000 skin ailments[44,45]. This technological breakthrough enables the development of diagnostic tools that are efficient, precise, and easily accessible. These tools can assist healthcare providers and individuals in detecting early stages of skin cancer, particularly melanoma. Consequently, this significantly enhances the chances of successful treatment and improves patient outcomes. AI-driven solutions show significant potential in the continuing battle against skin cancer, as they enhance medical competence and contribute to improved and easily accessible healthcare for everyone.

1.9 AI in The Diagnosis and Treatment of Brain Tumours.

In recent years, AI has made notable progress in diagnosing and categorizing brain tumours. MRI is now the most reliable and widely accepted method for identifying and describing tumours. Traditional MRI techniques, such as T_1 and T_2 weighted imaging and fluid-attenuated-inversion-recovery (FLAIR) sequences, have the drawback of providing non-specific contrast enhancement and a high probability of failing to detect tumour infiltration in particular areas[46]. AI has improved the accuracy and speed at which radiologists can identify diseases, decreasing the time required for diagnosis. Machine learning techniques have also been used to study different CNS tumours, namely brain metastases and CNS lymphoma[47]. These techniques can provide clarity in cases when diagnosis is uncertain and enhance the efficiency and accuracy of workflow. AI techniques exhibit significant potential for advancing radiology and precision medicine due to their capacity to identify patterns and integrate data beyond human capability. An optimal AI-driven diagnostic system for neuro-oncology would integrate all pertinent multimodal imaging data with clinical information and molecular markers to accurately forecast biologically grounded and clinically significant subtypes for a novel tumour diagnosis, aligning with the precision medicine initiative. CNN-based DL can accurately identify brain tumors just a few millimeters in size. Additionally, it can differentiate between Glioblastomas (GBMs) and brain lesions that have spread from other parts of the body[48]. Radiomics is a novel topic in neuro-oncology that has emerged from integrating clinical, histological, and radiological data with ML/DL image processing techniques[49]. AI-based radiomics enables rapid histopathologic classification/grading of tumors, improving noninvasive tumor characterization. This technology allows for quick assessment of prognosis, tracking of therapy response, and evaluation of tumours even during surgery. AI algorithms can analyze these photos at the pixel level, enabling them to extract imperceptible information from the human eye and facilitating more precise grading. Radiomics encompasses a series of intricate multi-step procedures that include manual, automated, and semi-automatic segmentation. The conventional histological assessment of cranial tumours involves the identification of microscopic characteristics such as neovascularization, central necrosis, endothelial hyperplasia, and areas of infiltration[50]. These factors sometimes intersect and may result in inaccurate positive outcomes. To address this intricate nature, digital slide scanners are being used to transform microscopic slides into picture files that are then analyzed by AI-driven algorithms like Support Vector Machines (SVM) and decision trees. SVMs have shown superior accuracy rates. The AI algorithms use genetic and molecular indicators, such as isocitrate dehydrogenase (IDH) mutation status, to examine pathological specimens of gliomas and forecast their fates.

1.10 AI Applied in the Field of Radiation Oncology.

Radiation therapy is a vital element of cancer treatment and is advised for about 50% of individuals[51]. Although technology has made significant progress, certain components of the radiation treatment procedure still need laborious manual input from various healthcare experts, such as radiation oncologists, medical physicists, medical dosimetrists, and radiation therapists. Studies have shown that deviations in the treatment planning procedure for radiation might detrimentally affect the overall survival rate, even in the context of clinical trials[52]. To do tasks that typically require human intelligence, such as decision-making, pattern recognition, visual perception, and problem-solving, at a comparable or higher level of competency, artificial intelligence (AI) covers the creation and application of complex computer algorithms. Radiation treatment may encounter several issues; which AI can help by revolutionizing many medical fields. This enhances the accessibility and effectiveness of cancer care globally[53]. The radiation oncologist determines the appropriate dose of radiation for the tumour and sets limits on the amount of radiation that can be delivered to surrounding organs before treatment planning. However, variations in the biology of the tumour can lead to significant differences in its sensitivity to radiation, even within the same type of cancer. AI platforms have the potential to personalize radiotherapy by predicting the tumor's sensitivity to radiation and determining the optimal dose that can be achieved with a specific treatment plan, based on the shape of the tumour and organs. AI has been used to generate synthetic CT images from MRI images of the brain and pelvis, and the resulting treatment plans showed minimal differences in radiation dose[54]. Technological advancements have also allowed for integrating MRI scanners with linear accelerators, opening up new possibilities for using MRI to guide radiation therapy. By generating high-resolution pictures from low-field-strength MRI scans, the employment of AI in therapy technologies, especially in MR Linac, offers a chance to improve the visibility of tumors during therapy[55]. The effectiveness, repeatability, and standard of radiation therapy planning may significantly increase. Automated segmentation techniques, such as those created for modeling oropharyngeal, primary lung, and nasopharyngeal carcinomas, may be made possible by AI and might eventually result in almost automated procedures[56]. As a result, fewer appointments, including consultations, will have to be made for individuals in the radiation oncology department. Planning the radiation dosage, administering the therapy, and doing the follow-up examinations takes time. Long wait times make individuals anxious and negatively affect the clinic's productivity and patient satisfaction[57]. AI can pinpoint the critical elements that affect waiting times, such as the time of day, the number of radiation dosage fractions, the median length of prior treatments, the number of treatment fields, and the length of prior treatments. AI may improve the clinic's efficiency and flow by foreseeing waiting periods. Figure 2 shows a typical CADx workflow for detecting prostate cancer.

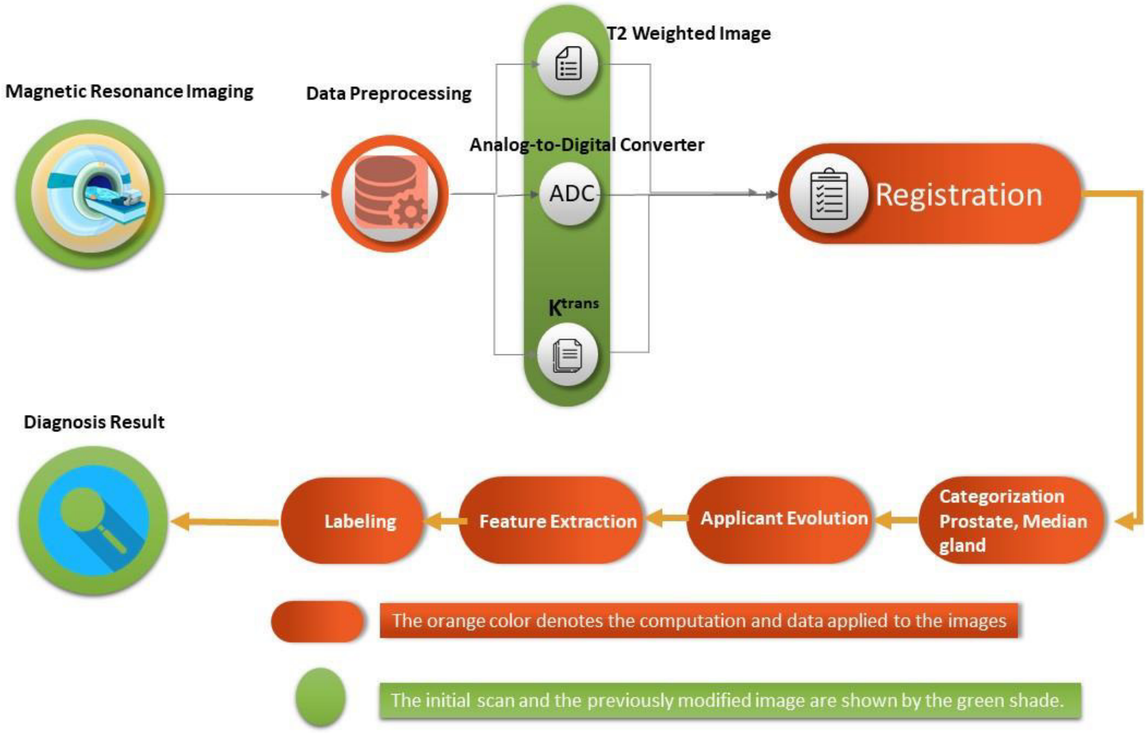

Fig: 02 A typical prostate CADx system's flowchart

2. CHALLENGES IN THE USE OF AI IN THE FIELD OF ONCOLOGY

The fast growth of AI demands doctors to keep up to speed and appreciate the medical consequences of emerging technologies. Physicians must develop and nurture the essential talent of being digitally literate and proficient in critically assessing clinical evidence in the age of AI[58]. All is essential for all doctors need to acquire knowledge about AI and grasp its core concepts. AI has the potential to significantly change and revolutionize certain elements of modern medicine by allowing the analysis of vast quantities of unorganized data, encompassing preclinical investigation, pharmaceutical exploration, clinical experimentation, and even ordinary clinical procedures, including communication. AI may exhibit bias via several means, such as the inherent assumptions made by AI engineers during development and the presence of bias within the training data utilized[59]. If the training data is obtained from a uniform population, it may have limited applicability, which might worsen racial or ethnic inequalities, as an example. Therefore, it is crucial to include a wide range of ethnicities, age groups, and genders, along with instances of both benign and malignant tumours, throughout the AI training process. Inorder to effectively incorporate precision medicine and AI into practical clinical environments, one must consider environmental variables, constraints on healthcare in underprivileged areas, and several medical conditions. Another potential source of bias arises when radiologists' interpretation is considered the "gold standard" instead of the true ground truth or the definitive conclusion of the case, whether benign or malignant[60]. For developing future models that effectively tackle the ethical dilemmas and obstacles associated with integrating AI into current systems, it is crucial to possess a comprehensive understanding of these difficulties. Significant challenges and inquiries persist, encompassing the onus of standardizing, collecting, and managing data; the inherent bias in training data sets; the absence of robust reporting standards; the limited number of prospective clinical validation studies; challenges in user-design and workflow implementation; outdated regulatory and legal frameworks surrounding AI; and the rapid expansion of knowledge and dynamic data. AI algorithms trained on one system's data may exhibit reduced performance when applied to data from a different system. Implementing standardized terminology and data-gathering methods would enhance the integration of oncology into electronic health record (EHR) data, which is crucial for ensuring that AI may have a significant and meaningful influence on cancer[61]. Optimally, data standardization before algorithm creation is advisable for data collection. Patient-reported outcome measures (PROMs) are optimal for gathering standardized data directly from the patient early in the process. Within the field of cancer, Patient-Reported Outcome Measures (PROMs) are now used to detect first indications of patient discomfort and to assess the standard of healthcare[62]. Nevertheless, these measures encounter similar obstacles to their deployment as those previously mentioned. AI is susceptible to social bias, which refers to inequalities in healthcare delivery that consistently result in suboptimal results for certain populations. For instance, if an AI model was created to aid pain management, the algorithm might generate less accurate predictions specifically for black patients. Since AI relies on hidden or unclear factors as input variables, explaining the reasoning behind the predictions and determining when they are illogical becomes challenging. The lack of standardized reporting in AI has led to a reproducibility issue, potentially impeding the mainstream acceptance and use of AI. AI-based solutions may possess adaptability or versatility, and the end-user must perceive the dynamic nature of these solutions. The widespread use of AI technologies in medicine is hindered by the often mentioned "black box" character of the process, especially when it comes to DL- and neural network–based systems that depend on complex hidden layers of data interaction[63]. Conventional statistical techniques evaluate connections between variables and conduct hypothesis testing in a certain direction, whereas AI seeks to simulate intricate systems and provide precise predictions[64]. Despite the significant growth in cancer-related AI algorithms and sophisticated CDSS, there is a lack of study on their prospective validation in ordinary clinical practice, whether to substitute or enhance human intelligence[65]. Integrating AI models into cancer practice should be grounded on empirical research, ensuring that they lead to decreased morbidity and death rates and/or achieve comparable therapeutic results more efficiently. The patient group selected for implementing and using these models should accurately represent the population from whom the training data were collected. Failure to do this and the excess or under-representation of certain groups or situations may result in biased sampling, leading to subpar model performance, erroneous predictions, and even possible injury.

3. CONCLUSION

Investigation is required to comprehend the impact of AI on patient outcomes and expenses. Moreover, significant obstacles hinder the adoption of AI in the field of cancer, including the full spectrum of oncology treatment. Training and educating the oncology workforce, establishing uniform data sets, research reporting, validation methodologies, and regulatory requirements, as well as funding and conducting future research, will need a substantial interdisciplinary endeavor. Therefore, it is crucial to form alliances across healthcare systems, academia, business, and governmental agencies to effectively use AI in the field of cancer during the era of big data. The research emphasizes that AI increasingly influences several scientific disciplines, such as cancer and its associated domains. To devise effective development plans with tangible outcomes, it is crucial to begin by comprehending the historical context and assessing the existing accomplishments. As shown, AI has already been integrated into oncology clinical practice, but ongoing and intensified efforts are necessary to harness AI's capabilities. From our perspective, the crucial challenges for successfully concluding the "AI revolution" in oncology are establishing multidisciplinary/integrative developmental perspectives, recognizing the significance of all neoplasms (including rare tumors), and the ongoing support to ensure its advancement.

4. AUTHORS CONTRIBUTION STATEMENT

Ammar A. Razzak Mahmood conceived the study and was responsible for the overall direction, analysis, and planning. Dr Roopa Murgod Scarried out the implementation. Saswat swarup Badapanda took the lead in writing the manuscript. Dr. John Abraham provided critical feedback, reviewed, and helped in the final corrections of the manuscript.

5. CONFLICT OF INTEREST

Conflict of interest declared none.

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