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Current trends of artificial intelligence in cancer imaging

Verde F *et al*. AI in cancer imaging

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Abstract

In this editorial, we discussed the current research status of artificial intelligence (AI) in Oncology, reviewing the basics of machine learning (ML) and deep learning (DL) techniques and their emerging applications on clinical and imaging cancer workflow. The growing amounts of available "big data" coupled to the increasing computational power have enabled the development of computer-based systems capable to perform advanced tasks in many areas of clinical care, especially in medical imaging. ML is a branch of data science that allows the creation of computer algorithms that can learn and make predictions without prior instructions. DL is a subgroup of artificial neural network algorithms configurated to automatically extract features and perform high-level tasks; convolutional neural networks are the most common DL models used in medical image analysis. AI methods have been proposed in many areas of oncology granting promising results in radiology-based clinical applications. In detail, we explored the emerging applications of AI in oncological risk assessment, lesion detection, characterization, staging, and therapy response. Critical issues such as the lack of reproducibility and generalizability need to be addressed to fully implement AI systems in clinical practice. Nevertheless, AI impact on cancer imaging has been driving the shift of oncology towards a precision diagnostics and personalized cancer treatment.

Key Words: Artificial intelligence; Machine learning; Deep learning; Oncology; Medical imaging; Cancer imaging

INTRODUCTION

In this new era of health-related technology and medical advances, artificial intelligence (AI) has put down roots making it possible to teach computers to do an intelligence human task, thus emerging as a problem-solving tool in data analysis and improving many aspects of clinical care[1,2].

Machine learning (ML) is a subset of AI that develops computer algorithms to make predictions or decision tasks without prior explicit programmed rules. ML algorithms use iterative static methods learning from "training" data to progressively improve the model performance over time. Based on the type of learning, ML is generally divided in (1) supervised learning, which uses labelled training data to map the expected outputs; (2) unsupervised learning, which deploys unlabelled data to learn new patterns; and (3) reinforcement learning, considered as a subfield of ML using reinforcement tools in a dynamic setting[3] (Figure 1). The supervised method is the most used ML technique in medical imaging applications and, relying on the relationship between input features and expected outcomes, the ML algorithms are grouped into three broad categories: Linear, Nonlinear and Ensemble, as described in Table 1. Furthermore, based on the data features exploited by the algorithms, ML can be applied to handcrafted features as predefined features in the data set, or to non-handcrafted features, involving raw data as part of the learning process[4]. Deep learning (DL), is a subgroup of ML techniques using non-handcrafted features and it is composed of artificial neural networks (ANN) modelled as neuron multi-layered networks allowing to automatically extract features without prior labelling and perform high-level tasks[5]. The most common ANN used in medical image analysis is based on convolutional architecture [convolutional neural networks (CNN)], consisting of hidden multi-layers that compute and filter high dimensional data to obtain the correct outputs, such as detection and characterization of tumoral lesions on imaging examinations[6].

AI-based approaches have been investigated in many fields of oncology, from imaging to histopathological and molecular diagnosis. Indeed, encouraging results have been obtained in cancer imaging, especially in screening environments. Among the different available imaging modalities, computed tomography (CT) and magnetic resonance imaging (MRI) are the most widely employed due to their prominent role in oncologic patients for staging, treatment monitoring and follow-up. Moreover, the introduction of advanced imaging techniques such as perfusion CT, MRI and MRI-diffusion-weighted imaging could provide the addition of functional over morphological data to further characterize tumor phenotype and behavior. Of note, radiology and oncology share the need for precision diagnosis and prediction models, by using cross-valuable multiple parameters from medical images and clinical data. The current applications of AI in cancer imaging include the optimization of the clinical-radiological workflow (patient screening, image acquisition) and also more specific image-based tasks (cancer detection, characterization, and treatment monitoring).

In the next sections we introduce the possible applications of AI in oncology imaging (Table 2).

Clinical-radiological workflow empowerment

AI techniques can enable the aggregation of clinical and imaging data to improve screening programs' efficiency, due to the possibility to analyse a large volume of different types of data including clinical risk factors, genetic data, and imaging examinations. Breast cancer surely represents a leading area of AI development, in particular in screening practices as demonstrated by recent studies that explored the impact on clinical practice of ML model in identifying individuals at increased risk of breast cancer[7,8]. Indeed, a recent study of Ming *et al*[9] investigated the performance of different ML-based techniques in predicting breast cancer risk using clinical and genetic risk factors in comparison to the Breast and Ovarian Analysis of Disease Incidence and

Carrier Estimation Algorithm (BOADICEA) risk prediction model; decision ML-based models yielded better results in classifying cancer from non-cancer cases and increased the predictive accuracy by 20%-25% including equal risk factors used in the BOADICEA model. Moreover, considerable differences between the BOADICEA and risk-based ML models were observed in terms of classification for mammography surveillance according to the Swiss Surveillance Protocol, confirming the feasibility of ML prediction models in the clinical-imaging decision workup[9].

Regarding imaging acquisition and pre-processing, DL methods have shown an important impact on the reduction of radiation dose in CT examinations[10] and have been used for improving magnetic resonance imaging quality with the potential to decrease acquisition time[11].

Cancer detection

Recent evidences of AI applications include breast cancer detection in mammography, tomosynthesis, and MRI as well as identification of CT lung nodes, brain tumors, and prostate cancer on MRI.

Among these, mammographic detection of breast cancer represents a challenging image analysis task because breast cancer could be masked by healthy breast tissue. In a recent study[12], a DL AI system provided by Google Health company outperformed the radiologists involved in the mammographic screening from multiple centres in the United Kingdom (UK) and United States (US). The AI system yielded absolute reductions of 1.2% and 2.7% in false-positive and false-negative rates, respectively, in the UK test set and 5.7% and 9.4% in the US dataset. Moreover, the AI system exceeded the average performance of six expert radiologists who interpreted a sample of 500 randomly selected cases in a controlled study[12]. Similarly, Rodríguez-Ruiz *et al*[13] demonstrated that radiologists improved their diagnostic performance in detecting breast cancer on screening mammography examinations with the use of a DL-based AI system. In detail, the authors observed that radiologists improved their average area under the receiver operating characteristic curve (AUC) from 0.87 to 0.89 (P = 0.002).

In the field of lung cancer, recent research showed that a DL automatic detection algorithm achieved higher performance than the radiologist group in the detection of malignant pulmonary nodules on chest radiographs; moreover, radiologists' performance improved when DL algorithm was used as a second reader[14].

Tumor segmentation, characterization and staging

Segmentation represents one of the most challenging tasks of oncological image analysis and AI algorithms have allowed the development of systems that can enable automatic tumor segmentation. Recently, DL networks, such as CNN, have been applied in segmentation tasks gaining accurate results regarding radiotherapy treatment planning, volume measurements and, monitoring disease progression[15,16]. Indeed, increasing evidence in recent literature has highlighted the high performance of DL models in performing fully automated whole-breast segmentation to obtain reliable and robust methods for quantitative imaging analysis[17,18].

High-performance levels of AI algorithms in handling multi-dimensional data have allowed extracting and analyzing radiomic biomarkers reflecting image tumor heterogeneity thus empowering precision diagnosis and staging in cancer imaging[19] (Figure 2). For instance, with our research group, we used a combined model of MRI radiomic features and ML analysis to differentiate typical and atypical adenomas from non-adenoma adrenal lesions, which showed a better performance than the radiologist assessment[20]. Further, our group assessed the usefulness of an ML-based radiomic approach applied to MR imaging to differentiate high- from low-grade clear cell renal cell carcinoma achieving accuracy greater than 90%[21]. Reliable results and robust evidence have been providing in lung cancer diagnosis as showed in a recent work of Beig *et al*[22], which proposed a radiomic-based ML algorithm using non-contrast lung CT to distinguish non-small cell lung cancer adenocarcinomas from benign granuloma, resulting with outperforming results of AI system in comparison to the radiologists' evaluation (accuracy = 75% *vs* 61%).

Staging represents a crucial point of the oncological workflow to delineate the most appropriate treatment in a personalized and precision way. In this view, recent pilot studies have been carried out on the staging of primary tumor size, lymph nodes involvement, and distant metastasis[23]. For example, our group investigated the clinical feasibility of a combined approach of radiomics and ML-based on MR images for the identification of deep myometrial invasion in endometrial cancer in a clinical context; indeed, the integration of the developed ML algorithm improved radiologist accuracy from 82% to 100%[24].

Treatment monitoring

Temporal follow-up of tumors as wells as the treatment response are active fields of research of AI technology to find accurate models for evaluation of efficient anticancer therapies that increase the progression-free survival of patients. In this regard, excellent results have been obtained using AI radiomics MRI-based models in predicting survival and recurrence-free survival in breast cancer[25]. Moreover, the development of AI models has been explored in breast cancer imaging to assess predictive image-based phenotypes for precision medicine, in particular to predict the response to neoadjuvant chemotherapy (NAC). In a recent study, Sutton *et al*[26] explored the usefulness of a combined radiomics MRI-based and molecular subtype-based ML model in assessing the complete pathological response (pCR) to NAC; their AI model accurately predicted pCR on MRI with an AUC of 0.88 and showed that the performance in predicting pCR increased when radiomics features were combined with molecular subtype in comparison of the solely molecular subtype results[26].

CHALLENGES AND FUTURE DIRECTIONS

AI techniques still have to face some issues to be incorporated in clinical practice. Of note, large datasets containing annotated images are needed for training of DL algorithms, but standardized imaging workflow lacks[15]. Complex AI functions are not easily interpreted by healthcare providers, and this "black box" nature could affect the acceptance of AI programs, also from the ethical and legal points of view[27]. Moreover, variability across multi-center and multi-vendor should be addressed with future studies sharing more reliable and robust validation[28].

Despite these drawbacks, AI incorporation into cancer imaging has been boosting the shift of oncology towards a precision diagnostics and personalized cancer treatment. Indeed, as previously discussed, recent literature evidence pointed out the emerging role of AI in supporting all cancer imaging pathways from screening programs to diagnostic and prognostic tasks, offering new methods to increase radiologists' performance in order to improve oncological care environment. Furthermore, the integration of AI into molecular pathological epidemiology can aid in developing pathologic signatures to stratify patients' risk and predict biological tumor behavior by using clinical, radiological and pathological data[29]. In the future, collaborations between different expertise figures, such as oncologists, epidemiologists, radiologists, pathologists and data scientists, should be encouraged to achieve harmonized and integrated development of AI systems in cancer research.

CONCLUSION

We have provided an overview of AI integration in cancer imaging, focusing on the basics of this disruptive technology and on the significant results obtained in improving clinical and radiological workup for oncological patients. Although, more evidence is still demanding the outlook of AI in cancer imaging remains bright.

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Figure Legends

Figure 1 Diagram showing different categories of artificial intelligence.

Figure 2 A schematic diagram of a radiomic and machine learning workflow pipeline applied to contrast-enhanced computed tomography images.

Table 1 Most commonly adopted alghoritms in supervised machine learning

ML technique	ML alghoritms	Description
Linear	(1) Linear regression; and (2) Logistic regression	Linear methods are used to modelling the relationship between the dependent variable and one or more independent variables
Nonlinear	(1) Naive Bayes; (2) Decision tree; (3) k-Nearest Neighbors; (4) Support vector machines; and (5)Neural network	Nonlinear approaches are used to produce predictive insights depending on nonlinear relationships in experimental data
Ensemble	(1) Random forest; (2) Bootstrap aggregation; and (3) Stacked generalization	Ensemble techniques stack multiple models in order to improve prediction robustness and provide more accurate predictions than any individual model

ML: Machine learning.

Table 2 Possible clinical applications of artificial intelligence in oncological imaging

Clinical application	Oncologic field	Imaging modality	AI technique
Clinical-radiological workflow	Breast cancer[9]	Mammography	ML
	Image acquisition[10,11]	CT, MRI	DL
Cancer detection	Breast cancer[12,13]	Mammography	DL
	Lung cancer[14]	X-Ray, CT	DL
Tumor segmentation	Breast Cancer[17,18]	MRI	DL
Tumor characterization	Adrenal cancer[20]	MRI	ML
	Renal cancer[21]	MRI	ML
	Lung cancer[22]	CT	ML
Tumor staging	Head and neck cancer[23]	CT	ML
	Endometrial cancer[24]	MRI	ML
Treatment monitoring	Breast cancer [26]	MRI	ML

CT: Computed tomography; MRI: Magnetic resonance imaging; AI: Artificial intelligence; ML: Machine learning; DL: Deep learning.

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