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Editorial

Focus issue: Artificial intelligence in medical physics

1. Preamble

Following on the European Federation of Organisations for Medical Physics (EFOMP) editorial on Artificial Intelligence in relation to the medical physics profession [1], and in order to meet the educational needs of the Medical Physicist (MP) in this new area of AI, EFOMP announced in June 2019 the creation of a 2 years Working Group (WG) entitled "Artificial Intelligence (AI)". The expected outcomes are an AI for Medical Physicists (MPs) Curricular and Professional Program as well as an EFOMP European School of Medical Physics Expert (ESMPE) AI module.

EFOMP identified the need for Medical physicists (MPs) to take up their stakeholders' role in the era of AI in medicine, by updating their training and education programs. This is also clearly stated in the EU RP174 presenting European Guidelines on Medical Physics Expert and strengthening the importance of education and training as the foundations of the MP profession [2].

It is within this context that the EFOMP WG on AI proposed to the Editor-in-Chief of EJMP a focus issue (FI) dedicated to AI in medical physics. The idea was to gather in one Physica Medica volume the most important topics addressed in the curriculum, for the education and training of European Medical Physicists (MPs). Having received the enthusiastic approval of the Editor, who suggested to widen the scope of this Focus Issue to current research aspects in the field of AI, we were asked to act as Guest Editors. We were honoured and humbly accepted the task.

This FI aims at providing a summary of the techniques and applications of AI in medical physics. It also addresses common pitfalls associated with these technologies. Because the application of AI in medicine in general and in medical physics in particular has seen an unprecedented increase in the recent years, the medical physicist profession has to keep pace with these changes, and we hope that this Focus Issue will provide a guide for MPs who are, or will be involved, in this exciting field.

2. Content of the volume

Twenty-seven papers (out of the 32 invited) were finally accepted for this Focus Issue. The table of content of this issue is meant to introducing MPs, through review and original papers, to the pillars of knowledge, development and applications of AI, in the context of medical imaging and radiation therapy. It is certainly not exhaustive, and it lacks some important topics like ethical aspects of AI or a methodological paper on the integration of AI applications in the clinical workflow, which unfortunately did not make it through the peer-reviewed process of the invited contributions. Because of the restrictive timeframe for the FI there was no possibility to include new contributions on these topics.

As the curricular program developed by the WG was almost ready at the time the FI was conceived, it was also included as an invited (and accepted) paper. The FI starts therefore with it and the following articles are presented in a sequential way that reflects the curricular structure.

2.1. The medical physicist curricular and professional programme to include Artificial Intelligence

The curricular programs for MPs are organized per sub-specialties. The curriculum on AI developed by the working group (Zanca et al.) is not meant to replace them, but rather expand the sub-specialties' ones on topics related to AI [3]. It has been subdivided in two levels, Basic and Advanced, depending on the potential involvement of the medical physicist in specific applications of AI and hence allowing for tailored education. The aim of this Basic training level is to introduce MPs to the pillars of knowledge, development and applications of AI, in the context of medical imaging and radiotherapy. The Advanced level instead, aims at building deeper expertise in the same topics. This paper is an extremely important contribution to the education of medical physicists in AI as the curriculum presented could be used not only as a module of the ESMP but also as a guideline for the programs of national organisations, members of EFOMP. Note that surveys had been performed to assess the perceptions of MPs towards relevance and impact of AI [4].

Avanzo et al. [5] presented a survey of research articles in AI applications in medical imaging produced in 2015–2020 by authors with scientific affiliation in Italy, also in collaboration with the task group "AI for Medical Physics" of the Italian Association of Medical Physics (AIFM). This represents the first attempt to review this research field in Italy by the medical physics community, with an analysis of 168 studies. The vast majority (71%) was in the field of diagnostic imaging (MRI, CT, radiography, mammography), and prevalently aiming at image classification tasks (57% of the articles) and then at image segmentation (16%), using deep learning in only 35% of the cases. These findings confirmed for the Italian framework the well-known rapid growth of the research interest in AI technologies by the international medical physics community in very recent years. They also pointed to possible difficulties in assembling and accessing large databases of images best suited for analysis by deep learning AI methods. This concern was also shared at EU level with specific research calls dedicated to building large repositories of freely available medical images for AI applications.

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2.2. The pillars of AI knowledge for MPs

In Montero et al. [6] a review of the building blocks of AI methods, together with their application to medical imaging is given. A key section is the one describing the state-of-the-art of AI methods such as Machine Learning (Ml) and Deep Learning (DL) for medical imaging analysis, completed by interesting interpretation on the evolution needed for having such AI applications really breaking through in clinical practice. An overview of such ML-based applications in the literature is given by Strigari et al. [7]. The manuscript highlights more than 188 scientific papers and discusses some limitations and opportunities of AI application in the clinical practice for future research. The authors identified common factors such as research area, discipline, number of images reported in the study for validation, number of patients analysed, type of images, codes and algorithms used, primary and secondary purposes of the studies. Regardless of the field of work, the reader can easily find and identify his/her own study discipline and have an immediate overview of the state of the art of the literature of the last 5 years on which to identify his/her research and amount of data needed in the field of medical imaging applied to AI.

When it comes to developing such applications, as reviewed by Castiglioni et al. [8], each of the phases required for building them has its specific challenge. Researchers in AI need to collect a large set of high quality labelled and annotated data, as the accuracy of AI tools depends largely on the dataset used for training. Harmonization techniques can minimize error due to heterogeneity when dealing with data from multiple centers, for instance. In radiomics studies, overfitting of machine learning can be prevented by careful feature selection before ML. Deep neural networks composed stacks of layers of nonlinear units are more challenging due to the infinite possibilities of arranging neurons into different architectures. Methods to estimate sample size in AI are still under investigation, however, data augmentation can deal with small and imbalanced datasets, and transfer learning – the use of pretrained AI tools adapted to the task at hand – can be applied as a less demanding alternative to training a DL network from scratch.

To illustrate the aspect of data preparation, a comprehensive guide to open access platforms and tools has been described by Diaz et al. [9]. They explain in detail a typical medical image pipeline, i.e. deidentification, data curation, centralised and decentralised medica image storage, and data annotation tools. They provide a comprehensive guide to choose among the armamentarium of currently available tools and platforms towards developing and or applying AI algorithms.

Next to in-house developed AI application, commercially available ones are also increasing and dealing with the procurement, commissioning and integration in clinical workflow of such tools poses important challenges. Bosmans et al. [10] proposed a framework to facilitate medical physicists' role in the introduction of AI solutions in clinical practice. Focus was given to the procurement process including acceptance, commissioning and QA of AI tools. On the AI regime, these steps require further consideration and dedicated test methods as compared to the tradition radiological equipment procurement process. The nature of AI based tools warrant specific Key Performance Indicators (KPIs) and metrics defined for systematic set of clinical cases (in acceptance) and ensuring suitability to local clinical environment (in commissioning). Insight of the expected performance of new clinical AI tools may also be surveyed from scientific publications or published data-sets with representative data, with similarity to local workflow. Quality assurance of AI tools is needed to ensure the stable performance of these algorithms especially concerning the upscaling usage and upgrading with self-learning networks. All these aspects indicate new and additional challenges which must be taken into account while considering continuous professional development of medical physicist and our role in hospitals.

Both for in-house developed and for commercially available applications, an effective regulation is crucial to enable a safe and optimal embedding of AI-based medical devices in the clinical settings. As described in Beckers et al. [11], in May 2021, the European Medical Device Regulation (EU MDR) will become fully applicable and AI-devices with an impact on patient diagnosis or treatment fall under such directive as well, when classified as medical devices. The paper summarizes the new regulatory roadmap comprising the intended use, risk classification, clinical evidence generation and post-market surveillance. With such knowledge, MPEs will be able to effectively participate on the purchase, commission and introduction of AI-based tools in the clinical workflow. As noted in the paper, one of the main pitfalls at present is the existence of very few guidelines for commission and acceptance of AI based medical device software, noting the urgency for initiatives from national and international medical physicists' professional organizations to solve this gap.

Last but not least, the review of McCarthy et al. [12] provides insights into recent enterprise imaging solutions applied to medical physics and healthcare settings. The rise in big data has opened up numerous opportunities for the application of enterprise imaging solutions to big data issues of healthcare. The review summarizes the key tools and approaches of enterprise imaging and big data in clinical practice and has a considered discussion of the steps required to implement a clinically based enterprise model. Insights are provided into how solutions must address compliance, improve patient care, cost effectiveness, healthcare workflow and the AI platforms. The key challenges of systems integration, governance and data privacy/security is also highlighted in line with clinical value and efficacy of the electronic health records. The use of AI can expediate patient care and reduce healthcare costs, but the management of system accuracy, stability and reproducibility must be considered with specialist training and continuous professional development of medical physicists to ensure appropriate care of patients and regulatory compliance.

2.3. AI applications in CT and NM

The integration of AI in x-ray and emission CT for fast and accurate diagnosis of difficult lesions looks promising. These new AI applications, however, require proper validation, as their reliability and robustness are critical for patient outcome. In Buls et al. [13], a FDA approved commercial AI tool with real-time clinical workflow integration was assessed for diagnosis of intracranial hemorrhage (ICH) and pulmonary embolism (PE) on a two retrospective cohorts of contrast enhanced pulmonary angiography and cranial non-contrast CT exams of 500 patients each. The AI tool was able to produce accuracy 0.93 (0.90–0.96) for ICH and 0.98 (0.96–0.99) for PE, showing potential to rule out ICH and PE in diverse clinical settings with substantial concordance between AI and expert reading.

Computer aided diagnosis in Low dose CT, the most common modality for lung cancer diagnosis, is of paramount interest for lung cancer screening. In Astaraki et al. [14] an AI pipeline to classify lung nodules in low-dose CT as malignant or benign which uses a convolutional neural network (CNN) to extract image features combined with a machine learning classifier was implemented. The features were extracted using supervised training. The models were trained in a publicly available database and resulted in high performance (0.936 Area under the Receiver Operating Characteristic (ROC) curve) in cross validation, which outperformed the classification performance of the Kaggle 2017 challenge winner.

Quality assurance of AI tools in imaging rely on the use of specific phantoms for measurements in reproducible and controlled conditions. Cisbani et al. [15] designed a phantom with capability of contrast medium injection and inserts of different sizes for testing AI in CT imaging, They tested deep learning architecture based on modified U-net for denoising or segmentation, and investigated dependency of performance on dose from CT scan, showing potential for studying patient dose reduction achieved by AI-based image quality improvement.

Conditional generative adversarial networks (cGAN) are a promising AI tool which generates images. Funama et al. [16] explored the use of cGAN for generating a 55 keV CT from a standard 120 kVp CT of enhanced abdominal imaging. The obtained images provide improved contrast of iodine compared with the surrounding tissues, in terms of peak signal to noise ratio and structural similarity index, showing how synthetic images generated by cGAN can improve diagnostic performance.

The applications of AI in nuclear medicine focusing on both single-photon emission computed tomography (SPECT) and positron emission tomography (PET) imaging were reviewed comprehensively by Arabi et al. [17], with emphasis on deep learning (DL) algorithms, now used on a broad range of applications. They presented DL algorithms and architectures used in SPECT and PET acquisition, reconstruction, and quantitative imaging for different purposes such as AI-assisted image interpretation, decision support, image segmentation, registration, and fusion, diagnosis and prognosis as well as radiomics and precision medicine. The AI-based internal radiation dosimetry in radionuclide metabolic therapy using PET and SPECT is also discussed. Of note, the AI approaches are presented from the point of view of the MP and emphasis on understanding their advantages and limitations as processing and/or decision support tools.

2.4. AI applications in RX, mammography

As two-dimensional X-ray imaging is the most common medical image, AI is expected to have significant impact in this field. Nouisianen et al. [18] investigated the use of CNN to automate diagnostic chest radiography quality control, assessing different image quality features on patient images (lung edges inclusion, patient rotation, and correct inspiration). The areas under the ROC curve were >0.88 for the lungs' inclusion, and >0.70/>0.79 for the rotation and the inspiration, respectively. Such an approach is proposed as an automated quality control of radiographies, which could help reducing unnecessary image repetition and patient dose.

AI-based techniques have demonstrated to be important tools not only for radiologists but also for MPs and estimating dose from medical imaging is among MPs' most critical responsibilities. Breast dose from mammographic procedures is typically quantified as mean glandular dose (MGD). Its estimation requires measurements of breast density, air kerma and Monte Carlo-based conversion coefficients. By use of deep neural networks Tomal et al. [19] showed that both volumetric breast glandularity and mean glandular dose could be automatically assessed. The system was thoroughly validated by virtual anthropomorphic breast phantoms and other tools available in the literature. The developed tools and databases used, are made available for the Medical Physics community by contacting the corresponding author.

Finally, Ricciardi et al. [20] introduced a system for the automatic classification of the presence/absence of mass lesions in digital breast tomosynthesis (DBT), based on a deep convolutional neural network (DCNN). Three DCNN architectures were compared with state-of-the-art of pre-trained DCNN architectures (AlexNet and VGG19) on two different radiology datasets. A Gradient-weighted Class Activation Mapping (Grad-CAM) technique was also implemented, which, by visualizing false color maps over the areas in the image at risk of presence of a lesion, can facilitate tumor localization. This work could be further extended to also include localization of masses and microcalcifications within the tomosynthesis images.

2.5. AI applications in MRI

With its excellent soft tissue contrast, MRI is key for the diagnosis, management and treatment planning of patients, and AI applications to MRI imaging are seeing rapid pace of evolution. In the review of Montalt-Tordera et al. [21], the authors summarize the clinical applications, major drawbacks, and current trends of ML approaches used in MRI reconstruction. By focusing on AI for image formation, they identify current machine learning (ML) approaches used to populate the k-space and/or image space in clinical images in order to speed up what is an inherently a slow acquisition process. The resulting image quality enhancement, and its potential for translation into clinical use are discussed. In a clinical setting, quality measurement of MRI images is the role and responsibility of MPs.

Among others, MRI-based AI methods are expected to improve diagnosis in Neurooncology, with impact on diagnosis, therapy and follow-up. Zegers et al. [22] review the requirements for AI applications to generate fully synthetic CT data for radiotherapy planning, pathology classification or patient outcome prediction and identify the core knowledge. The original research papers reviewed by the authors were classified based on their applications, into three categories: technological innovation, diagnosis and follow-up and the applications ranged from improving the acquisition, synthetic CT generation, auto-segmentation, tumor classification, outcome prediction and response assessment. The authors identified the novel fields and potential broad range of applications, the applicability across institutions and the requirements for robust validation of the implantation of technologies in clinical practice.

Another AI application with clinical impact in MRI is presented by Ritz et al. [23], where they evaluated deep learning models for the detection and characterization of medial and lateral meniscal tears. The combined architecture 3D convolutional neural networks reached AUC values of 0.84–0.95 for meniscal tear detection and migration. External validation of the models resulted in an AUC of 0.89, demonstrating a high performance in knee menisci lesion detection and characterization.

2.6. AI applications in RT

Radiotherapy is another hotbed for AI applications, promising to automate and speed up the entire workflow from patient positioning to treatment planning and plan verification. Heddens et al. [24] investigated deep learning applications in breast cancer radiotherapy performed in a 3D conformal fashion. They configured a modified U-net to predict the optimal dose distribution, that is, the dose from a treatment plan, whose beam configuration has been optimized to meet the prescribed dose constraints. The resulting dose map can be used as a reference dose for automatic plan generation.

Barragan et al. [25] investigated the factors influencing deep learning dose prediction for IMRT of esophageal cancer. They investigated the effect of different LINACs, beam arrangements and energies, and tested robustness of dose after recontouring, concluding that dose accuracy depends on data size and quality. This is a typical example of how AI is currently already in the stage of creating complex treatment plans.

Radiotherapy is inherently linked to diagnostics and utilising diagnostic data (especially from CT, MRI and PET) in therapy planning and guidance. Therefore, various AI applications and methods which have been developed and implemented in previously described studies are also affecting and improving the radiotherapy processes which can be seen as a large-scale platform for AI data-driven patient care.

2.7. Applications in US

Tsai et al. [26] use a DL approach to diagnose pleural effusion on clinical lung ultrasound videos. Their proposed algorithm resulted in high accuracy (91.1% for videos, 92.4% for frames) compared to clinical standards, allowing fast and robust diagnosis irrespective of the competence of the sonographer performing the examination. This study is a step towards full automation of lung ultrasound evaluation for lung pathologies.

2.8. AI applications in radiomics

Papadimitroulas et al. [27] describe the status of the research on AI for extracting image biomarkers from medical images, a field currently termed radiomics. The authors review the major interpretability methods that help overcoming the black box issue, enabling explainable AI for classification and prediction in clinical practice. They also discuss the crucial requirement of multicenter recruitment of large datasets, increasing the biomarkers variability, so as to establish the potential clinical value of radiomics and the development of robust explainable AI models.

In Maffei et al. [28] a radiomics features classifier was implemented to evaluate segmentation quality of heart structures, to drive auto-contouring optimization. Twenty radiomics features were found to be robust across structures, and the trained AI Classifier detected correct and incorrect contours with an accuracy of 82.6%. The proposed workflow allows an automatic assessment of segmentation quality and may accelerate the expansion of an existing auto-contouring atlas database as well as improve dosimetric analyses of large treatment plan databases.

3. Concluding remarks

This FI of Physica Medica reflects the interest of the scientific community and the professional organizations represented by EFOMP in AI by reviewing the techniques and the particular applications of AI in medical physics as well as the current limitations and the challenges yet to overcome. The need for basic education or continuous professional development of medical physicists to cope with the increased use of AI solutions in medical physics is also discussed making thus the work presented in this FI of high interest for the readers of Physica Medica.

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