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Invited Commentary

Artificial Intelligence and the Medical Radiation Profession: How Our Advocacy Must Inform Future Practice

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ABSTRACT

There is no escaping the fact that academics are devoting unrelenting attention to the impact artificial intelligence will have on health care. Radiological and radiation oncology organizations worldwide are devoting their time and resources to ensure their members are both informed and prepared for the inevitable changes to the respective professions. This commentary provides an overview of how artificial intelligence will affect medical radiation professions of both diagnostic and radiation therapy streams. It outlines how these professions can play an active role in ensuring optimal outcomes for the well-being of both the workforce and the patients.

Keywords: Artificial intelligence; radiology; medical imaging; radiation therapy; precision medicine

Introduction

Artificial intelligence (AI) is a dominant subject weighing on the minds of medical radiation professionals. Advancements in deep learning, particularly within the field of image analysis [1], combined with improved computational power, are changing the way health care is both managed and perceived.

The enormous quantity of imaging and associated data produced by the medical radiation sciences has sparked the interest of some of the largest technology companies in the world. AI firms are seeking to access patient data for the purpose of training deep learning algorithms to automate tasks such as image classification and segmentation [2–4]. Even the human trait of empathy is explored as a potential, reproducible quality to enhance the patients' experience via the use of "chatbots" [5]. The discussion surrounding the use of AI in health care has generated differing sentiments with respect to the future viability of the medical radiation profession [6]. One must only observe the myriad editorials [7–10] to understand the narrative that AI will replace jobs is, in the present trajectory, unfounded. Nonetheless, AI's utility as an optimization tool is not. Medical radiation professionals must approach AI similar to the way they have approached advancements in the past; with cautious optimism, and an appetite to be involved. Radiological organizations, such as the Canadian Association of Radiology, the American College of Radiology, the American Society for Radiation Oncology, the European Society for Radiation Oncology, and the Radiological Society of North America (RSNA), have taken noteworthy steps to ensure their members are informed, with the RSNA developing the first scientific journal dedicated to AI in radiology, titled "*Radiology: Artificial Intelligence*" [11]. For medical radiation technologists in Canada, the Canadian Association of Medical Radiation Technologists has initiated an AI subcouncil of the professional practice advisory council, working to seek advice and better educate their members surrounding this technology. Investment into AI research in medical imaging in 2019 is projected to surpass $500 million US dollars, a significant rise from the $80 million in 2016 [2,4]. Following the day-to-day developments of this field of research can be confusing and tiresome. Similar to the 24-hour news cycle, a story breaks [12]; bold claims are made [13], and, as the dust settles, the facts are scrutinized [14]. If one were to examine the events of the news as a yearly recount, rather than an hourly bulletin,

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one might form a broader, more general understanding of significant events. This commentary article will aim to inform the reader in a similar vein.

Examples of AI in Medical Radiation Technologists Practice

Medical Imaging

From assessing the diagnostic quality of a radiological image to interpreting its contents and leveraging that information, medical imaging professionals use heuristic techniques in weighing complex factors related to each clinical decision. It should come as no surprise that one of the more prolific areas of AI research in medical imaging is the investigation into the viability of deep neural networks to interpret and classify radiological images. There is no "one size fits all" algorithm; researchers are instead tailoring machine learning models to detect and/or classify specific pathologies, including pulmonary nodules [15,16], wrist fractures [17,18], pediatric elbow fractures [19], and intracranial hemorrhage [20,21].

The results of such studies, within their experimental setting, are impressive, and it is suggested that these algorithms will primarily be used as triaging tools to prioritize worklists by acuity [22]. Comparisons can be drawn to the concept behind radiographer alert systems used within the United Kingdom [23] and Australia [24], where abnormal images are flagged by the radiographer in an attempt to optimize the triaging process. However, unlike AI-led image triaging, frontline image interpretation by radiographers has been established and used in the clinical environment for many years [25–27] with measurable, positive outcomes [28,29]. Given the eventual widespread use of AI-led radiographic image triaging, one may believe the role of radiographers interpreting images on the frontline could be redundant; in fact, this exact sentiment has been expressed in contemporary literature [30]. If AI-led image abnormality detection systems become viable clinical tools, could the radiographer's scope in the patient's treatment pathway, be extended? Rather than waiting for a diagnostic report to be produced, frontline staff such as radiographers could act on flagged abnormalities and expedite patient treatment pathways. We have the clinical experience and knowledge to work in this capacity; whether we choose to take on this role will depend on our willingness to act. For the time being, studies published in this field have been observational and predominantly retrospective [31,32]. There is a lot of research, yet very little clinical validation [33].

Radiation Oncology/Therapy

Several applications for the use of AI are emerging along the radiation therapy workflow and across the multidisciplinary radiation oncology practice. Given the ability of AI to perform decision-based, repetitive tasks, research has begun in several areas along the patient journey [3]. Contemporary methods of automated segmentation of tumours and organs at risk still require human oversight and editing. This is one such area where machine learning may be used to improve the current workflow. The use of convolutional neural networks to improve auto-segmentation has shown impressive results when outlining the organs at risk, yet found the volume segmentation of contouring different shaped tumours more difficult [3]. Inverse treatment planning in radiation therapy uses a computer to develop a treatment plan based on an objective with constraints. Although the computer can solve the optimization, a human planner is still required to adjust the constraints to yield a high-quality plan. Applying machine learning algorithms trained on dose-volume histograms, datasets, and other plan factors has transformed traditional inverse planning into intelligent treatment planning [34]. These examples highlight the more obvious applications of AI in the radiation therapy department; however, novel applications of AI are being explored beyond image datasets.

Radiation therapy depends on information from multiple, often-siloed, data sources and is heavily reliant on rigorous quality control. Although not authentic machine learning, Yang et al attempted to overcome the balkanization of information, developing an algorithm that reviewed the electronic chart. Integrating multiple disconnected systems and analyzing data varying in format from Digital Imaging and Communications in Medicine to text, the program identified and flagged discrepancies for users to review [35].

Our ability to connect with our patients, through informed understanding of their situations, has also seen interest in AI research. Chaix et al studied the interactions of breast cancer patients with a "chatbot" named "Vik." Vik was created to interact with breast cancer patients via text message and responds to not only fears and concerns but can also provide prescription reminders. There is no question that human empathy and companionship are irreplaceable, yet of the 4,737 patients studied, prescription compliance was higher in the study arm, and 93.95% recommended Vik to their friends [5]. This study, although promising for the development of "chatbots," also reminds us that patients desire focused care and support. As the field of radiation therapy becomes increasingly data driven and inherently precise, we should remember that behind all the numbers and Kaplan-Meier curves is a human being. Artificial intelligence may improve the efficiencies of the cancer treatment pathway, but there will always be a need for educated professionals such as radiation therapists to provide informed advice and the indispensable element of human support.

The results of novel AI studies published in the past 5 years have been promising, yet as a whole are lacking in real-world clinical validation and application [31–33]. There is no doubt that the technology will reach a stage where clinical application influences a patient's care; however, much like with the development of new drugs, regulators, and health care professionals alike must work to ensure there is an agreed-upon methodology in the approval and use of AI as a clinical tool [36].

Ethics and Future Considerations

AI tools proposed for clinical practice are full of promise, and the development of these tools has captured the attention of major radiological societies around the world. The ethics behind the use of artificial intelligence in medical imaging is complex and beyond the scope of this commentary. For the interested reader, several white papers and position statements explore these issues in detail [22,37,38]. The quality of the data on which these algorithms are trained is essential in ensuring safe use. Supervised learning algorithms require a substantial collection of radiological data, validated by experts, and widely agreed upon by both the medical radiation science and the computer science community [39]. Even so, data that are well validated is still only fit for the population from, which it is retrieved [33]. An intriguing challenge in the future will be the effects of population stratification on the algorithms trained [31]. Will vendors be transparent about the population groups used for training [37,38]? How narrow will their algorithm's purpose of use be? Should AI companies be held accountable if it is not made clear to the user the risk of dataset shift or algorithmic bias [37]? Will a pneumothorax detection algorithm developed in America perform well in a country such as India [33]? These catechisms of responsibility are as much for the regulators as for the medical imaging community to consider.

Responsibility of the Medical Radiation Profession

It has become the responsibility of the medical imaging community to ensure responsible use of data. The American College of Radiology has made considerable strides to ensure there is validated, publicly available data for researchers [40], and the RSNA is even holding competitions on those to promote the democratization of AI research [41,42].

Our experience as medical imaging professionals is invaluable when assessing the viability of AI tools. Efficiencies gained through AI can be capitalized on in several ways, and objectives related to "more time with patients" could be in direct competition with objectives related to reduced wait times or higher throughput. Given the increased workloads faced by health care providers [43,44], products promising greater efficiency could seem like a panacea. However, one must consider the current concerns surrounding burnout in the health care industry [43–45]. Could these promises be likened to the offer of a faster conveyer belt in an assembly line where workers are already struggling to meet demand? Medical radiation professionals are well-positioned to advocate for an ideal balance here. Our priority must be ensuring that any tools suggested for implementation in our workplaces will result in a healthy balance between efficiency and the well-being of both patients and those providing care.

With this field of innovation rushing toward widespread implementation, it is not unreasonable to feel a sense of helplessness. One unfortunate characteristic of our profession seems to be the tendency to underestimate the influence we can have on our own work environments. So how do we, as a community, ensure we do not stand idly by during this technological revolution? As frontline healthcare professionals, we understand more than most the impact changes in technology can have on both workflow and patient care [46–48]. Medical radiation professionals have hands-on experience from all stages of the patient journey, from emergency diagnosis to complex cancer treatment. We must make our voice heard during vendor demonstrations and conferences and ultimately in our research [49]. Rather than whisper in the corridors of our respective workplaces, we must find the courage to share information with confidence. If a new application changes practice, why not audit that change and publish it? If a vendor's promise seems suspiciously ambitious, who better to enquire and advise than the professionals operating their product daily [50]? No barriers are preventing medical radiation professionals from learning more about the nuances of AI in their respective industries. As with any new technology, history will be kinder to those who embrace change and endeavor to learn [51]. That is not to say that full immersion in the subject is necessary; simply keeping an eye on current research [52] and engaging in discussion with your peers around the topic could make all the difference.

Ultimately, professional organizations such as the Canadian Association of Medical Radiation Technologists, Australian Society of Medical Imaging and Radiation Therapy, The European Federation of Radiographer Societies, and the Society and College of Radiographers must develop their own strategies for approaching AI, since their members will be looking to them for resources such as white papers, position statements, and educational material. Some medical radiation professionals are already consulting with industry organizations [53], publishing AI-related research [54–56], and playing an active role in ensuring AI is used safely and responsibly. Professional organizations and members alike should look to these individuals for inspiration as to how we, as a profession, can improve. If we want our voices to be heard, we must first speak up. If we chose not to, this ship will sail regardless, perhaps just not in the direction we want it to.

Conclusion

Medical radiation science has seen many transformative events over the years: the digital age, the three-dimensional age, and now we enter the age of AI with the same challenges and optimism as before. We also face this new era equipped with the lessons we have learned in the past. As medical radiation professionals, we possess unique clinical experience and research talent. Harnessing this talent to ensure AI is used both safely and ethically is vital. There are enough computer scientists to write new algorithms; what we require are engaged health care professionals, making their voice heard to ensure that the overall outcome of this technological revolution is for the greater good of society.

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