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The Need for a Machine Learning Curriculum for Radiologists

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INTRODUCTION

Machine learning (ML) is an emerging technology that is on the verge of transforming the practice of radiology. As new algorithms are being developed for an increasing number of medical imaging and operational applications, radiologists will be expected to effectively interpret model output as a part of their daily practice [1,2]. It is therefore imperative that imaging experts understand the potential, as well as the limitations, of ML, to appropriately integrate it into the clinical workflow. However, a framework for educating the next generation of radiologists on how to interface with ML technology has not been established, leaving radiologists potentially ill prepared to fully leverage these tools safely and effectively [3,4].

THE JUSTIFICATION FOR A CURRICULUM

Just as the understanding of medical image creation forms the basis for radiologic interpretation, algorithmic understanding provides the foundation for the use of ML in clinical radiologic practice. Although radiologists are currently expected to understand the imaging process from the production of ionizing radiation in a CT scanner to the visualization of a pixel on their monitor, there is currently no such standard for ML, despite early clinical deployments that are already underway [4,5]. If radiologists are expected to utilize ML models safely and effectively for imaging interpretation, education for all levels of background and experience will be required, and a formalized ML curriculum targeted toward early career radiologists and trainees is urgently needed.

Inspired by the education provided for other aspects of radiological training [6], an ML curriculum should consist of all stages of model development, model translation, and use in clinical practice. This includes the data collection and annotation process, algorithm selection, model development and training, model validation and assessment, requirements for clinical translation, interpretation of performance metrics and model output, and identification of modes of model failure. Just as radiologists must be able to leverage their knowledge of the image formation process to identify, interpret, and account for imaging artifacts, the ability to critically evaluate various algorithms' strengths and recognize their potential pitfalls will be essential to determine the validity and clinical applicability of their predictions. Therefore, a working knowledge of these concepts is critical for radiologists using ML tools to augment imaging interpretation, as well as for other tasks performed at various points along the imaging chain (eg, image examination ordering, image acquisition protocols, and reporting) [1,2].

ML MODELS ARE NOT INTUITIVE

This need for a structured curriculum is exacerbated by the unintuitive ways in which ML models can fail. Classical regression techniques (eg, multivariate linear and logistic regression) are highly interpretable, thereby allowing for seamless introspection of their predictions. If the output of the regression is unexpectedly large, one can readily inspect each regressor to identify the contributing factor and attribute the source of error. Such is not the case for many ML models [7].

A random forest, consisting of a series of decision trees, can be analyzed by evaluating the output of each decision tree. However, each tree may leverage highly complex feature combinations at each decision node, making it difficult to attribute the source of a given prediction. A deep neural network, the

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de facto standard for recent imaging models, further compounds these difficulties. Because these networks may have millions of parameters and hundreds of layers, determining the contributing factor is often infeasible [7]. Although saliency maps may offer some degree of visibility into the most impactful pixels or voxels [8], they can also be misleading [9], making them challenging to rely upon in clinical practice.

As a result, the performance of these opaque ML algorithms may be highly unintuitive. A model may successfully identify a rather challenging imaging finding and immediately afterward misdiagnose a far simpler case. Although deep neural networks have been able to achieve high levels of accuracy in the ImageNet competition distinguishing between highly similar species of animals, they also can be fooled by adversarial noise that is imperceptible to the human eye [10]. Therefore, it is critical that radiologists learn to appropriately leverage a model's output, critically evaluating all findings while never becoming complacent or blindly accepting these algorithmic predictions.

RADIOLOGISTS ARE NEEDED FOR ALGORITHM DEVELOPMENT AND TRANSLATION

Because radiologists will consume ML algorithms in their daily practice, model output must be clinically relevant, valid in "real-world" settings, and easily accessible within the clinical workflow. Although even radiology trainees possess a detailed understanding of the clinical questions relevant to patient care and the radiology department workflow, the average engineer or data scientist knows very little about the practice of radiology or medicine.

To ensure ML algorithm predictions are valid and generalizable in patient care, radiologists should actively participate in model development by providing the clinical context, framing the imaging question, curating ground truth data sets, ensuring seamless deployment in reading rooms, and continuously monitoring and validating algorithm performance. Multidisciplinary collaboration with data science experts, software engineers, and referring clinicians will be critical to successfully harness the potential of ML in radiology. Furthermore, radiologists must be prepared to tackle the ethical, regulatory, legal, and economic challenges that will inevitably arise as this technology permeates the health care landscape [11]. To provide meaningful and informed feedback during these stages of model development and translation, radiologists will need to possess at least a basic understanding of the algorithms and the processes used by their collaborators. Ultimately, radiologists should couple their clinical expertise and knowledge of ML tools to develop and utilize this technology to the greatest benefit of patient care.

MOVING FORWARD

With this transformative technology already beginning to appear in hospitals worldwide, it is critical that radiologists be trained in its use. Fortunately, as one of the more technologically intensive medical specialties, there are many organizations, such as the RSNA's Radiology Informatics Committee, the Society for Imaging Informatics in Medicine's Machine Intelligence in Medical Imaging Online Group, and the ACR's Data Science Institute, that are well positioned to formulate a consensus curriculum among the nation's leading radiologists and imaging scientists to provide didactic material to meet the needs of the field. Such a proposed curriculum should be vetted by the ABR, the Association of Program Directors in Radiology, the ACGME's Residency Review Committee, and other relevant groups such that basic command of ML principles may become part of all radiology residents' core competencies and milestones. These interpretive and noninterpretive skills should be appropriately assessed via standardized evaluations, such as the ABR Core Examination, to ensure a fundamental grasp of the subject matter, which will be critical as these technologies become pervasive in daily practice. In addition, any ML educational efforts must span both trainees and attending physicians, and therefore accredited CME material should also be developed to ensure practicing radiologists stay abreast of the latest developments.

Careful thought must be given when developing an effective dissemination strategy. Delivering a standardized and robust curriculum at each teaching institution will represent a challenge, as programs may have faculty who are less well versed in this topic or lack the resources to organize formal training opportunities. To address these concerns, web-based interactive sessions accessible to all learners could be developed, modeled after existing online informatics courses, such as the National Imaging Informatics

Curriculum and Course, which was born from a partnership between the RSNA and Society for Imaging Informatics in Medicine.

Another challenge in implementing an ML curriculum in radiology residency is the rapidly evolving nature of the field and the dynamic regulatory, economic, and medicolegal landscape affecting the deployment of ML tools in clinical settings. Many of these areas still require considerable research and development, so an initial curriculum must remain flexible and be continuously updated to reflect new knowledge gains and policy changes. However, this reality also represents an exciting opportunity for radiology trainees to participate in scholarly work and innovative projects in this space. Given the potentially limited number of local faculty mentors, a national network of mentors could be established to allow exposure to these opportunities to trainees across the country.

CONCLUSION

The emergence of ML technology in radiology cannot be denied. Rather than succumb to fear and skepticism, future radiologists must be equipped with a working knowledge of ML to leverage the tools as they are deployed. To truly advance the standard of patient care, radiologists will not only be required to appropriately consume ML model output but also participate in its development and implementation to ensure that the most critical challenges in the profession are addressed.

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