ORIGINAL ARTICLE LEADERSHIP

Artificial Intelligence: Threat or Boon to Radiologists?

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Abstract

The development and integration of machine learning/artificial intelligence into routine clinical practice will significantly alter the current practice of radiology. Changes in reimbursement and practice patterns will also continue to affect radiology. But rather than being a significant threat to radiologists, we believe these changes, particularly machine learning/artificial intelligence, will be a boon to radiologists by increasing their value, efficiency, accuracy, and personal satisfaction.

Key Words: Machine learning, computer-assisted diagnosis/detection, value, efficiency, artificial intelligence

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Several recent articles have warned that machine learning (ML) or artificial intelligence is a significant threat to radiologists and radiology as a specialty [1,2]. In addition, two other significant threats, the move of patient care out of hospitals to outpatient locations and the changing methods of reimbursement, have also been identified. We agree that these trends, particularly ML and artificial intelligence, will lead to significant changes for radiology and how radiologists will practice. However, rather than leading to the diminished significance and value of radiologists, we believe that radiologists and radiology will continue to thrive. In fact, we believe that ML and artificial intelligence will enhance both the value and the professional satisfaction of radiologists by allowing us to spend more time performing functions that add value and influence patient care and less time doing rote tasks that we neither enjoy nor perform as well as machines. We address each of the identified threats in the following text.

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DEINSTITUTIONALIZATION OF HEALTH CARE

As detailed by Chockley and Emanuel [1], patient care is moving out of hospitals and into outpatient settings such as ambulatory surgical centers, outpatient imaging centers, urgent care facilities, and even patients' homes. In addition, readmissions of hospital patients are also being significantly decreased because of the combination of incentives and penalties embedded in the Patient Protection and Affordable Care Act. Chockley and Emanuel argued that this move out of hospitals may have dire consequences for radiologists by leading to a decrease in demand for imaging. In fact, this move away from inpatient imaging and toward outpatient imaging has already happened to a significant degree. On the basis of publicly available data from the *Neiman Almanac* concerning Medicare Part B, inpatient imaging volume decreased by 36% from 2006 to 2014 [3]. Outpatient volume during the same time period decreased by 6% whereas imaging volume resulting from emergency department visits increased by 38%. In 2006, inpatient volume accounted for 28% of all imaging volume, but by 2014 it accounted for only 21%. Revenue from inpatient volume decreased by 31% from 2006 to 2014 and accounted for only 10% of all imaging revenue in 2014. Even with the loss of additional inpatient volume that is not counterbalanced by an increase in outpatient volume, the effect on radiology and radiologists is likely to be minimal. In fact, if additional imaging volume is

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switched from inpatient care to outpatient imaging, there may be a positive effect on revenue for radiologists. Because outpatient imaging equipment is often owned by radiologists, they can receive both technical and professional revenue at outpatient centers, whereas hospital equipment is most often owned by hospitals, limiting radiologists' revenue to only professional revenue.

PAYMENT REFORM

Chockley and Emanuel [1] also cited the move from pure fee for service to alternative payment methods such as bundled care or pay for performance as a significant threat to radiology and radiologists. They believe that these payment models will lead to decreased demand for imaging, thus leading to decreased demand for imagers. It is clear that the move from pure fee-for-service payment models to alternative models, especially those that make ordering physicians responsible for the cost of imaging, will decrease the demand for unnecessary and "wasteful" imaging. Additional factors that will also decrease imaging demand include the introduction of clinical decision support systems that are incorporated into clinical physician order entry systems to ensure that only appropriate examinations are performed. What is unclear, however, is that the elimination of unnecessary examinations is truly a threat to radiologists. As the population continues to age and as more sophisticated imaging techniques are developed, the loss of unnecessary and inappropriate examinations may well be counterbalanced by an increase in necessary, valuable, and appropriate imaging examinations.

In addition, a recent study demonstrated that between 1999 and 2010 growth in the number of images per examination was disproportionately increased compared with growth in imaging utilization [4]. Although cross-sectional imaging volumes increased by a factor of 2, the number of images that needed to be interpreted increased by a factor of 10. On the basis of imaging volumes and the number of images per examination, the study calculated that the average radiologist needed to interpret one image every 3 to 4 seconds to meet the volume demands. Since 2010, the number of images per cross-sectional imaging examination has continued to increase because of improvements in both hardware and software, with some examinations now routinely consisting of more than 1,000 images. Therefore, even if imaging utilization may decrease because of the elimination of inappropriate ordering of imaging, the workload of radiologists and, consequently, the demand for radiologists will most likely not be significantly decreased.

It is true that a decreased number of imaging examinations and a move to alternative payment models, such as pay for performance, that emphasize value over volume might lead to a decrease in radiologists' salaries. However, this emphasis on value rather than volume will also be a factor that protects radiologists from obsolescence. There is no doubt, as discussed in the next section, that machines will replace several functions radiologists currently perform, particularly quantification, segmentation, pure pattern recognition, and data mining. However, the value of radiology and radiologists is far more than the sum of those functions. Radiologists' added value includes the correct protocoling of examinations, participation in multidisciplinary conferences, the integration of imaging results with other aspects of a patient's care such as pathology and laboratory results, and clinical findings. In addition, as exemplified by Imaging 3.0™ [5], radiologists are having more extensive interactions with patients. These interactions include explaining the results of imaging examinations and, in many cases, especially involving interventional procedures, taking primary responsibility for the care of patients. In addition, radiologists are becoming more integrated within clinical care teams, with reading rooms embedded into clinical floors and offices [6]. Machines "trained" in pattern recognition or data extraction will not be able to perform these value-added functions and therefore will not be able to replace radiologists. Rather, they will be an aid, allowing radiologists to perform even more of these value-added functions.

ML: ULTIMATE THREAT OR SAVIOR

Given the many scientific articles, newspaper and magazine articles, and even TV ads about ML, big data, data mining, artificial intelligence, and so on, it is not surprising to see a plethora of articles dramatizing these technologies' influence on medicine in general and radiology in particular. How can radiologists ignore IBM's Watson reading an x-ray during halftime of an NFL game? However, rather than decreasing the value of radiologists, we and others believe that computers using traditional or more sophisticated ML algorithms will be highly beneficial to our specialty, allowing us to be more operationally efficient and diagnostically accurate [7].

For radiologists, the key question is, "Can a machine learn to do what we, radiologists, do?" There are secondary, corollary questions with technological implications. "Can we teach a machine what we know and to do what we do?" These questions imply traditional computer algorithms using knowledge and instructions provided by the programmer. "Can a machine by itself learn what we know and to do what we do?" or even "Can a machine learn more than what we now know and use that new knowledge to make better clinical decisions?" These questions relate to contemporary ML algorithms. Whether a machine is taught or self-learns how to perform clinically useful interpretative tasks, the practical result is computer-assisted diagnosis and detection (CADD).

ML implies algorithms that can learn from and make predictions on the basis of new data. T. M. Mitchell [8] more fully described the concept: "A computer program is said to learn from experience E with respect to some class of tasks T and performance P if its performance at tasks T, as measured by P, improves with experience E." A theoretical example in radiology might be a new (minimal experience E) CADD algorithm that initially makes a correct diagnosis (task T) of breast cancer 80% of the time (baseline performance P). However, this algorithm has an ML component, and after being applied to 1,000 additional digital mammograms (additional experience E), its accuracy improves to 85% (improved performance P). The algorithm's performance is improved by the experience of the computer, without additional human interference. It learned on its own, just like a good mammographer who learns from his or her experience.

In general, ML algorithms create a computational model on the basis of example inputs to derive data-driven predictions or decisions. In the case of radiology, the main decision-making task is one of classification: given the images and available clinical information, what is the most likely diagnosis? There are innumerable CADD algorithms, many now using ML principles, that perform such classification tasks, though they differ in specific implementation, mathematical basis, and logical organization [9]. Regardless of the specific technology, the value of CADD is dependent on how accurately a given application makes diagnoses. CADD algorithm performance can be documented through statistical metrics with which radiologists are familiar, such as receiver-operating characteristic analysis. When, and if, the area under the curve of a CADD algorithm meets or exceeds that of a radiologist, the machine will have learned at least as much as radiologists now know and be able to help make decisions that we now make alone. In that case, we should and will incorporate that algorithm into our practice.

Most CADD algorithms are being developed for specific radiologic tasks such as detecting a pulmonary nodule or intracranial blood. The development of generalized ML algorithms that can replicate all of the functions of a human interpreter is much more difficult and, even if possible, will take significantly longer to accomplish. Some narrow ML algorithms have demonstrated areas under the receiver-operating characteristic curve exceeding that of house staff and board-certified radiologists. These algorithms have already started to be incorporated into clinical practice. For instance, ML algorithms incorporated into CADD products are now detecting pulmonary nodules, diagnosing colonic polyps, and screening for breast cancer, with much more to come [10,11]. In the not-so-far future, we believe these types of CADD algorithms will play a central role in radiology, being incorporated into routine workflow and providing real-time clinical diagnostic support on a daily basis. Although Watson and other CADD technologies are currently still struggling in the clinical environment [12], in 10 years it is possible that no medical imaging study will be reviewed by a radiologist until it has been preanalyzed by a "machine." Clinically validated ML technology integrated into radiology workflow will allow radiologists to more efficiently produce better quality reports. CADD will make us better radiologists, not replace us.

The incorporation of CADD into routine clinical practice will also lead to a significant gain in radiologists' efficiency. This gain will increase not only radiologists' productivity but also their personal satisfaction. It is unlikely that any radiologist entered the field with a desire to spend a large amount of time measuring lesions and doing segmentation. It is also probable that most radiologists do not enjoy the ever-increasing amount of time spent poring through electronic medical records in an attempt to garner relevant clinical information needed for appropriate protocoling and interpretation of examinations. There is little doubt that ML algorithms will be able to replace the majority, if not all, of the quantification tasks currently performed by radiologists as well as accomplish data mining of the electronic medical records in a more efficient manner. The widespread use of ML for these tasks will allow radiologists to spend their time performing value-added functions that cannot be performed by computers, and that will increase their professional satisfaction: integrating patients' clinical and imaging information, having more professional interactions, becoming more visible to patients, and playing a vital role in integrated clinical teams to improve patient care. It is likely, however, that the efficiency gain provided by CADD will lead to a need for fewer radiologists. Although we do not believe this will be a drastic decrease, we do believe it will be a noticeable change and will require appropriate reductions in residency slots. As competition for residency positions has been decreasing over the past several years [13], this will allow a better match between supply and demand for residency positions.

Although we believe that CADD will be integrated into clinical practice in a very significant manner in the next several years, there are several obstacles to the incorporation of CADD as a stand-alone device without radiologist oversight. The first is regulatory (FDA) approval. If a new device is believed to be substantially equivalent to a predicate device, one that has been previously cleared by the FDA, 510(k) clearance is possible. Submission for 510(k) approval requires a comparison of the new device and predicate device, explaining both similarities and differences, and why the differences should be allowed. If a predicate device does not exist, a manufacturer needs to obtain premarket approval (PMA). PMA standards are stricter than 510(k) approval and generally require formal clinical studies, which are expensive and time consuming. Modifications to a premarket-approved device may require a PMA supplement or a new PMA submission. This means that any alteration to an ML algorithm that was premarket approved may require an additional expensive and time-consuming approval process. Because of the expense and time required for PMA, 510(k) approval is the preferred method of regulatory clearance. This has significant ramifications for ML, as no predicate device exists that is used as a replacement for radiologists or human image interpreters. Conversely, algorithms or devices used to aid radiologists, such as mammography CADD, do exist. This has led current manufacturers of ML algorithms for image interpretation to describe them as aids to radiologists rather than replacements for radiologists. No manufacturer has been willing as of yet to spend the time or the money necessary to try to receive PMA. It is our belief that these regulatory hurdles will not be removed in the near future, thus leading to CADD's being used to augment and not replace radiologists.

In addition to regulatory challenges, there is the additional hurdle of patient acceptance of being treated and diagnosed by CADD rather than human physicians. It will be much easier to have patients accept algorithms that aid physicians rather than those that eliminate and replace physicians. Another industry that is also dealing with regulatory and psychological barriers to the acceptance of ML is the airline industry. Boeing's chief technology officer stated, "With respect to a commercial airplane, there is no doubt in our minds that we can solve the problem of autonomous flight. It's a question of certification procedures, regulatory requirements and, even more significantly, public perception. Will the flying public be comfortable getting onto a commercial plane with no pilot?" [14]. We believe these same hurdles apply to ML replacing human radiologists.

A final obstacle to CADD's replacing radiologists is the threat of significant liability to manufacturers when the ML algorithms make errors. Although the legal framework will need to be developed, it is likely that manufacturers of algorithms will be held responsible if ML algorithms, used by themselves without supervision by radiologists, miss significant pathology. It is far less likely that manufacturers will be held liable if these algorithms are only used to aid radiologists, not replace them. Unless the financial benefit to manufacturers is significantly greater for developing stand-alone algorithms than radiologist-aiding algorithms, it is unlikely that they will be willing to risk this added liability.

TAKE-HOME POINTS

- ML and CADD for imaging are progressing at a rapid pace and will soon be a part of routine clinical practice.
- CADD will perform several functions currently performed by radiologists today, such as quantification, segmentation, and preliminary pattern recognition. These will serve to augment and aid, not replace, radiologists.
- The gain in efficiency provided by CADD will allow radiologists to perform more value-added tasks, such as integrating patients' clinical and imaging information, having more professional interactions, becoming more visible to patients, and playing a vital role in integrated clinical teams to improve patient care.

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