Will Artificial Intelligence Replace Radiologists?

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> *The question of whether Machines Can Think is about as relevant as the question of whether Submarines Can Swim.*
>
> Edsger Dijkstra, 1984

As computer performance on complex vision tasks approaches that of clinical experts, radiologists look over their shoulders. Some of the ebullience for these new systems arises from the allure of creating beings in our own image (1). But the excitement is powered primarily by real innovation (2). Medical image analysis projects that once took years now can be completed in a matter of days or weeks. These huge leaps in computer vision have inspired dreams of health care transformation. But the extreme optimism often overshoots reality and dissipates during scientific "winters" of disregard (3). Artificial intelligence (AI) in radiology has, so far, followed this script.

The hype peaked in the year 2016: An oncologist and key architect of the Affordable Care Act predicted in the *New England Journal of Medicine* that "machine learning will displace much of the work of radiologists and anatomical pathologists" (4). Two Oxford economists indicated in the *Harvard Business Review* that machines will replace doctors because "when professional work is broken down into component parts, many of the tasks involved turn out to be routine and process-based. They do not in fact call for judgment, creativity, or empathy" (5). A luminary Stanford computer scientist and founder of the Google Brain Deep Learning Project forecasted in *The Economist* that radiologists would be replaced by AI sooner than their executive assistants (6). An AI pioneer who recently won the Association for Computing Machinery Turing Award opined, "We should stop training radiologists now" (7). Scientists crowed; radiologists cowered; ventures capitalized.

Many of these experts have since revised their thinking (8). Some now collaborate with radiologists to develop AI algorithms (9). But the eager pronouncements initially gave pause to medical students considering their specialty choices and spurred many radiologists to check their retirement accounts. The effect of computer vision on patient care is still mostly illusory, impeded by the scarcity of training data and the sluggish march to regulatory approval. No strangers to innovation, radiologists have confronted this supposed awful adversary, only to find what seems to be an amiable apprentice. As we ponder whether winter is coming for radiologists or for AI, the following parables may foretell the change of seasons.

Computer-aided Detection for Mammography: A Cautionary Tale

Concerns in the 1990s about the variable quality of mammography interpretation (10) led to two key steps forward: *(a)* the Breast Imaging Reporting and Data System (BI-RADS), arguably the most influential advance in the history of radiology communication (11), and *(b)* legislation to provide additional reimbursement for the use of AI to help radiologists detect breast cancer on mammograms. Radiologists flocked to purchase and deploy these computer-aided detection (CAD) systems (12). Recent persuasive evidence suggests that CAD systems have had no appreciable effect on the accuracy of radiologists (13). Perhaps the high rate of false-positive findings led to alert fatigue (14).

The recent rush of novel AI algorithms should prompt introspection about past failures of AI to live up to its promise. Today's AI tools have achieved regulatory clearance based on their performance at a small number of health care organizations. Perhaps the incremental accuracy of these new AI methods will reduce false-positive findings and blunt the "cry wolf" effect, but the generalizability of these algorithms to the diversity of radiology practices remains an open question.

Radiologists Master New Technology

As early as 1896, William Morton, a neurologist who popularized the use of x-rays in the United States, partnered with Edwin Hammer, an engineer who had mastered the electrical generators needed to produce the current for x-rays (15). Similar partnerships between clinicians and engineers were forged over each cycle of radiology innovation, including the advent of US, CT, and MRI.

When the first MRI devices were demonstrated, some speculated on the demise of radiologists. The high-contrast images made abnormalities obvious. As the theory went, patients would emerge from the imaging unit with clear results that could be managed by primary care physicians. Instead, we learned that these complex machines require extensive configuration to ensure the acquired images resolve the differential diagnosis. And the professionals interpreting the images must fathom how a device functions to distinguish artifact from reality (16). Training of radiologists began to incorporate MRI physics, now a mainstay of radiology residency. Radiologists can't construct an MRI device any more than a pilot can build an airplane. But radiologists learn to protect patients from the machine's weaknesses. As AI rises, organized radiology snaps into action once again. Radiologists are being trained to recognize AI's shortcomings and capitalize on its strengths (17).

Radiologists Know "The Long Tail"

We often compare AI algorithms to radiology experts based on the ability to identify a single disease (18) or a small set of diseases (19). These assessments dramatically oversimplify what radiologists do. A comprehensive catalog of radiology diagnoses lists nearly 20 000 terms for disorders and imaging observations and over 50 000 causal relations (20). An AI algorithm that diagnoses common chest conditions at the level of a subspecialty thoracic radiologist is a major step forward, an incredible asset to underserved regions, and could serve as a valued assistant for a subspecialty radiologist. But human radiologists are also trained to detect uncommon diseases in the long tail of the distribution, including rheumatoid arthritis, sickle cell disease, and posttransplantation lymphoproliferative disorder. AI is impressive in identifying horses but is a long way from recognizing zebras.

Even the simple act of measuring AI against radiologists, rather than measuring how AI might augment the performance of radiologists, perpetuates a misperception of AI's likely clinical role. Since the advent of diagnostic clinical decision support systems, human-machine collaborations have performed better than either one alone (21). Studies of radiology AI systems are no different (9).

The Mirage of Job Displacement

To illustrate the overreaction to technology's role in job displacement, venture capitalist Mary Meeker lists *New York Times* crywolf headlines from the past century (22): "March of the Machine Makes Idle Hands" (February 26, 1928); "Does Machine Displace Men in the Long Run?" (February 25, 1940); "200,000 Will Lose Jobs to Automation, U.S. Aides Say" (May 5, 1962); "A Robot is After Your Job" (September 3, 1980); "Will Robots Take Our Children's Jobs" (December 11, 2017). And yet, the steady march of increased employment continues (6).

Bank tellers are often cited as the canonical example of a job replaced by technology. But reliable studies of the industry show no such effect (23). In 1985, the United States had 60 000 automated teller machines (ATMs) and 485 000 bank tellers. In 2002, there were 352 000 ATMs and 527 000 bank tellers. The U.S. Bureau of Labor Statistics counted 600 500 bank tellers in 2008 and projects that this number grew to 638 000 in 2018 (24). Instead, bank tellers' responsibilities advanced from the drudgery of withdrawals and deposits at the bank window to more interesting and sophisticated transactions.

An Autopilot for Radiologists

Pilots must assimilate a torrent of information from a plane's sensors and from their own senses to make decisions on which human lives depend. Cockpits are designed to mitigate human failings and to complement the skills of pilots. Avionics digest complex information for easy human consumption. Displays and controls nudge pilots toward safety and warn against dangerous interventions. Pilots maintain equanimity because electronic monitors alert pilots to anomalous conditions. Tedious or repetitive tasks are handled by an autopilot. And yet, when a sensor malfunctions, a properly trained human pilot can look out the window and countermand the system.

The vision for AI in radiology looks much like a cockpit (25). Detection algorithms will solve "needle in a haystack" search problems, finding breast calcifications and lung nodules. Registration and segmentation tools will relieve the tedium of measuring and plotting the time course of liver metastases. Anatomic measurement apps will plot organ volume against the normal range. Classification routines will assist in resolving diagnostic dilemmas. And so AI will elevate the cognitive universe of radiologists to the top of their license—exercising judgment, creativity, and empathy as they interpret images in partnership with AI algorithms and patients (26).

Transformation of Radiology Work

Although the danger of AI to radiologists is overblown, the new medical computer vision industry will profoundly change how radiologists practice, most likely in a direction that pleases radiologists. And AI has the potential to democratize radiology by enabling nonradiologists in underserved areas to tap into subspecialty expertise, perhaps on their mobile devices. But the ethereal notion of an artificial general intelligence destined to replace us is just as fanciful today as attaching human qualities to submarines. As we are lifted by the latest AI bubble, "Will AI replace radiologists?" is the wrong question. The right answer is: Radiologists who use AI will replace radiologists who don't.

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