Review Article

Artificial Intelligence and Radiology in Singapore: Championing a New Age of Augmented Imaging for Unsurpassed Patient Care

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Abstract

Artificial intelligence (AI) has been positioned as being the most important recent advancement in radiology, if not the most potentially disruptive. Singapore radiologists have been quick to embrace this technology as part of the natural progression of the discipline toward a vision of how clinical medicine, empowered by technology, can achieve our national healthcare objectives of delivering value-based and patient-centric care. In this article, we consider 3 core questions relating to AI in radiology, and review the barriers to the widespread adoption of AI in radiology. We propose solutions and describe a "Centaur" model as a promising avenue for enabling the interfacing between AI and radiologists. Finally, we introduce The Radiological AI, Data Science and Imaging Informatics (RADII) subsection of the Singapore Radiological Society. RADII is an enabling body, which together with key technological and institutional stakeholders, will champion research, development and evaluation of AI for radiology applications.

Ann Acad Med Singapore 2019;48:16-24

Key words: Diagnostic radiology, Machine learning, Neural networks

Introduction: How Will Artificial Intelligence and Machine Learning Impact Radiology?

When a patient's diagnosis is uncertain, diagnostic radiologists study images created using X-rays, computed tomography (CT), ultrasound, and magnetic resonance (MR), to infer disease patterns and identify the most likely cause of the patient's signs and symptoms. The medical specialty of diagnostic radiology has always been greatly affected by advances in the fields of physics, medicine, biology and engineering, but is now also increasingly disrupted by innovations in computer and data sciences. Over the past few years, there have been abundant and frequent scholarly publications, news articles, and opinion pieces published on this subject. Some authors have gone so far as to predict the demise of diagnostic radiology as a specialty, if human image interpretation can be replaced by advanced machine learning (ML) techniques and big data analysis.[1]

Others see a brighter future for medical imaging experts by harnessing the power of artificial intelligence (AI) to augment human diagnostic abilities, especially in today's milieu of quantitative imaging biomarkers, precision medicine and value base radiology.[2] Radiologists are no strangers to disruptive technologies, having pioneered the translation of complex cross-sectional imaging technologies such as MR and positron emission tomography (PET) to clinical medicine, the digitisation of workflow in picture archiving and communication systems (PACS) and radiological information systems (RIS), and the incorporation of teleradiology and computer-aided detection

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(CAD) systems into practice.[3] So, what has changed? What does this potentially disruptive technology mean for radiology? And what lessons can we learn that can be applied to the rest of the medical community, for we all will surely be impacted by these rapid innovations?

AI can be defined as any technique that enables computers to mimic various aspects of human intelligence—including pattern recognition, data-driven learning, audiovisual perception, natural language understanding, knowledge-based reasoning, planning and control (Table 1). Although AI has a long and checkered history in medical applications stretching back to the 1970s, it is presently resurgent in the hype cycle, due to 3 factors: a) the availability of large-scale digital image databases, b) widespread availability of powerful general processing units (GPU)[4] and cloud resources, and c) the advancement of deep learning algorithms that enable computers to "learn" by mapping patterns in large amounts of data to their associated ground truth or labels.[5,6] In recent times, these artificial neural networks have achieved spectacular attention-grabbing headlines. Prominent examples include Google DeepMind's computer programme AlphaGo that beat a human expert at the board game of Go, Hanalytic's Biomind brain tumour diagnosis and test-taking robots that can pass medical examinations.[7,8] Some AI technologies such as facial recognition and customised predictive advertising, are already applied to our daily lives. For medical applications, deep learning has been successfully employed for interpretation of retinal images, skin lesion photographs and histopathological slides.[9] Notwithstanding the promise of AI for radiology, there is a need to learn from recent high profile missteps involving big data, ethics and privacy. For example, the breach of large-scale personally identifiable information by Facebook and Cambridge Analytica,[10] the development of dialogue systems that are susceptible to bias in training,[11] and the misuse of electronic surveillance[12] have caused considerable disquiet both to the general public and medical policymakers. Therefore, careful development and validation of these powerful tools for clinical medicine applications is crucial to optimise positive impact on large numbers of people, and prevent unforeseen or undetected effects. Hence, there is need for a strategic framework to guide the research, development and application of such powerful technologies in healthcare, so that big data and AI can be judiciously, safely and appropriately harnessed for the benefit of our patients.

Table 1. Common Definitions for Artificial Intelligence Terms

Nomenclature	Definition
Artificial intelligence	Techniques which enable computers to mimic various aspects of human intelligence – including pattern recognition, data-driven learning, audiovisual perception, natural language understanding, knowledge-based reasoning, planning and control.
Machine learning	A field of artificial intelligence that uses statistical techniques to allow computers to learn to make predictions from data.
Deep learning	A class of machine learning algorithms that employ a cascade of neural network layers to learn from vast amounts of data.

How Can Radiologists Use AI to Enhance Medical Diagnostics?

The value proposition of diagnostic radiologists extends far beyond mere image interpretation. Even before the first X-ray image is taken, important information about patient safety, radiation protection, pretest probability, appropriateness, study protocol and patient preparation, need to be processed using our understanding of medical physics, epidemiology and systems-based practice. These ancillary tasks entail radiologists working in teams alongside nurses, radiographers and technologists. Once the image is taken, radiologists must navigate through the image noise to distil the relevant signal, and only then, proceed to interpret the meaning of the image with reference to the patient's condition and the referring doctor's needs. Radiologists must also combine knowledge of false-positives (arising from artifacts or false signals), false-negatives (anatomic pitfalls, heuristics and cognitive biases that potentially lead to errors) with the timely communication of uncertainty, urgency, and unexpected findings. As such, radiology training and practice encompasses both crucial interpretive and non-interpretive (ancillary) tasks.[13]

Further, even the interpretive tasks in radiology extend well beyond the recognition of pathological patterns in images. Radiologists routinely employ "real" intelligence to convert accurate image interpretation into actionable, holistic patient-centric decision-making[14] in variable medical settings ranging from office-based outpatient private imaging centres, to tertiary academic research hospitals with complex casemix and comorbid patients whose care involve multidisciplinary team consultations and problem solving. Hence, the interpretive task of pattern recognition of pathological features within anatomical structures and extraction of biological meaning from low-contrast images (where contrast represents the difference between normal and abnormal structures, and the differences among many different causes of abnormalities) is only one, albeit important, part of the radiologists' workflow. Currently, it is mainly in this high-profile, thin slice of the diagnostic pathway, that AI is currently being focused. This, however, is set to change, and future interations of AI systems will conceivably combine multimodal sources of data, from imaging data to electronic medical records (EMR), as well as genomic and wearable sensor data.[15]

However, radiology can leverage AI technologies for both interpretive and ancillary tasks. The value proposition of AI is its speed and accuracy in detection, segmentation and classification of image features. Unlike humans, it does not suffer from fatigue, forgetfulness, nor social limitations of prescribed working hours. Potential use cases of narrow AI currently include tuberculosis and pneumonia detection in chest radiography[16,17] acute ischaemic stroke detection,[18] and radiographic bone age assessment;[19] the number of applications can only get larger. Outside the confines of image interpretation, AI can potentially have an even larger positive effect on the non-interpretive but resource-intensive ancillary imaging processes that take place in the background—for example, scanner and hospital workflows, decision support, and retrospective studies.

On the scanner front, as AI learns and implements ever faster and efficient methods of CT and MR image reconstruction, it is possible to realise abbreviated sequences and improved scanner productivity.[20] On the hospital workflow front, examples include smart data analytics in patient scheduling, decision support for safe and appropriate order entry, natural language processing-based querying and annotation of radiology reports, resource utilisation dashboards, and predicting healthcare economic trends. With neural networks capable of self-learning, constant and autonomous improvement and refinement of workflow can take place in the background.[21,22] A compelling case can thus be made that research and development resources for AI in radiology should focus on tasks that can yield larger net efficiencies, rather than on mere pixel-based computer-aided detection tools.

AI and Machine Learning: How is Singapore Responding?

Singapore radiologists have been adapting and innovating, building on previous experience, being early adopters of technologies such as PACS, voice recognition, teleradiology,[23] National Electronic Health Record (NEHR), and using computers in medical education and research.[24,25] Completed and ongoing projects in AI include abnormality detection in chest radiography, nasogastric tube detection on chest radiography (Fig. 1), automated fracture detection and labelling (Fig. 2) (Thian YL, personal communication), haematoma detection,[26] detection and quantification of midline shift in traumatic brain injury,[27,28] text-mining and natural language processing of radiology reports.[29]

In 2017, the Changi General Hospital Department of Radiology in partnership with SingHealth and Carestream Health, won the Ministry of Health (MOH) National Information Technolog (IT) Award in the 'Beyond Quality to Value' category for being the first hospital to implement an Artificially Intelligent module in the RIS to rightsite radiology reporting resources, ensuring higher quality

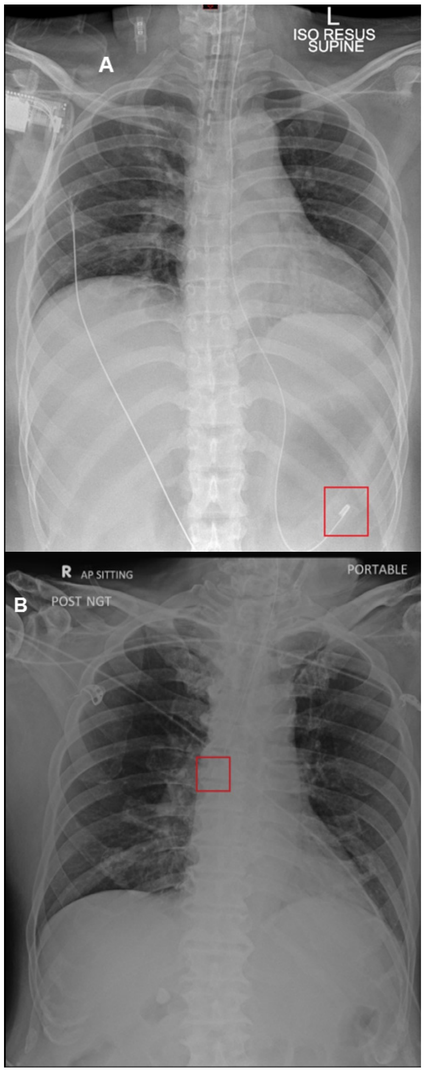


Fig. 1. Artificial intelligence (AI) for automated nasogastric tube (NG) tube detection. An AI convolutional neural network (CNN) is trained using a dataset of images enriched with radio-opaque NG tubes. It can subsequently detect and identify the position of the tip of the NG tube on a chest radiograph (red box) in these test/validation images. Images courtesy of Dr Charlene Liew, Dr May Lim, et al.

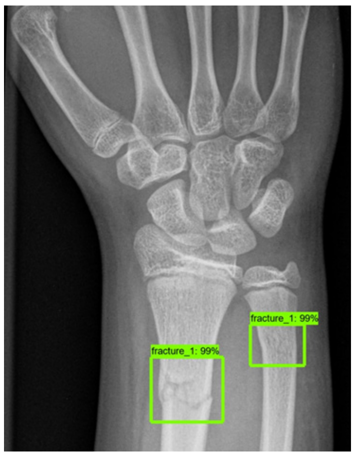
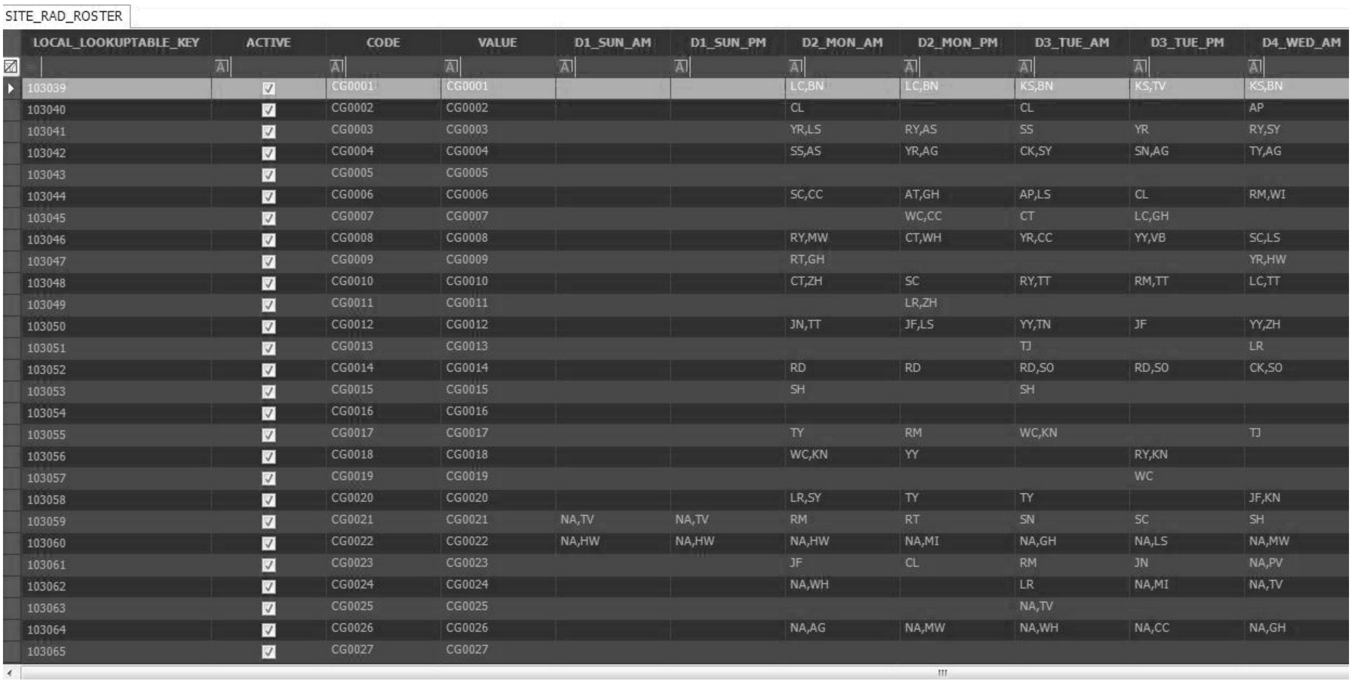


Fig 2. AI detecting distal radial and ulnar fractures in a child. Convolutional neural network trained using a dataset of fractures and normal radiographs, is able to localise both distal radius and ulna fractures with a confidence of 99%. Image courtesy of Dr Thian Yee Liang.

and faster report turnaround time for clinicians and at the same time increasing radiologist and radiographer work satisfaction[30] (Fig. 3). This system— albeit a rudimentary form of narrow, rules-based AI—nonetheless serves to highlight the potential of AI systems to automate non-imaging tasks in the radiology workflow, and future iterations may be enhanced with self-learning and self-improving AI models. The productivity gains from the system allowed radiologists, radiographers and administrators to spend more time in more pressing areas of patient care. This dovetails neatly into the 3 "Beyonds" initiative of the MOH to transform our healthcare landscape to meet the challenges of our ageing population, and illustrates the immense potential of radiologist-directed AI to streamline workflow and deliver better care to patients.[31]

Instead of a scattershot approach, the community of Singapore radiologists have formed a Singapore Radiological Society subsection for AI, Data Science and Imaging Informatics (RADII),[32] supported by the College of Radiologists, Singapore and the Academy of Medicine, Singapore to promote the research, educational and industrial aspects of AI, and to coordinate a national effort to align initiatives with national priorities. The recent Singapore Radiological Society Annual Scientific Meeting in 2018 featured dedicated sessions on Imaging Informatics and AI, bringing together local and international experts in radiology informatics, computer science research and industry to share ideas and experience. RADII teams in public healthcare institutions have also started formal and informal assessments of early FDA approved clinical AI systems and business models in the market, in order to understand the potential opportunities and challenges these nascent products offer.[33] Furthermore, a national coordinating body would be ideally placed to partner worldwide radiologist professional bodies such as the American College of Radiology, Radiological Society of North America (RSNA), Society for Imaging Informatics in Medicine (SIIM), Royal College of Radiologists (RCR)[34-37] and the wider medical community of ophthalmologists, dermatologists, cardiologists, endoscopists, and pathologists driving AI. RADII has established partnerships in particular, with the RCR to create AI imaging standards and guidelines, as well as participating in SIIM and RSNA international committees and Health Data Research UK (HDRUK) advisory workgroups.

Extensive translational research remains to be done in order to bring promising standalone performance testing results for diagnostic AI models into carefully evaluated and validated real-world clinical practice and meaningful outcomes.[38] There is an urgent need to develop means to standardise evaluation of AI algorithms, codify clinical guidelines for AI interpretation and reporting, and translate existing technology into reporting of real patient images. RADII—representing the stewards of data and resources within the AI radiological community—can consolidate and match clinical expertise with collaborators within the AI technology community in Singapore, including universities and research institutions like the National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LOCAL_LOOKUPTABLE_KEY	ACTIVE	CODE	VALUE	D1_SUN_AM	D1_SUN_PM	D2_MON_AM	D2_MON_PM	D3_TUE_AM	D3_TUE_PM	D4_WED_AM
103039	✓	CG0001	CG0001			LC,BN	LC,BN	KS,BN	KS,TV	KS,BN
103040	✓	CG0002	CG0002			CL		CL		AP
103041	✓	CG0003	CG0003			YR,LS	RY,AS	SS	YR	RY,SY
103042	✓	CG0004	CG0004			SS,AS	YR,AG	CK,SY	SN,AG	TY,AG
103043	✓	CG0005	CG0005							
103044	✓	CG0006	CG0006			SC,CC	AT,GH	AP,LS	CL	RM,WI
103045	✓	CG0007	CG0007				WC,CC	CT	LC,GH	
103046	✓	CG0008	CG0008			RY,MW	CT,WH	YR,CC	YY,VB	SC,LS
103047	✓	CG0009	CG0009			RT,GH				YR,HW
103048	✓	CG0010	CG0010			CT,ZH	SC	RY,TT	RM,TT	LC,TT
103049	✓	CG0011	CG0011				LR,ZH			
103050	✓	CG0012	CG0012			JN,TT	JF,LS	YY,TN	JF	YY,ZH
103051	✓	CG0013	CG0013					TJ		LR
103052	✓	CG0014	CG0014			RD	RD	RD,SO	RD,SO	CK,SO
103053	✓	CG0015	CG0015			SH		SH		
103054	✓	CG0016	CG0016							
103055	✓	CG0017	CG0017			TY	RM	WC,KN		TJ
103056	✓	CG0018	CG0018			WC,KN	YY		RY,KN	
103057	✓	CG0019	CG0019						WC	
103058	✓	CG0020	CG0020			LR,SY	TY	TY		JF,KN
103059	✓	CG0021	CG0021	NA,TV	NA,TV	RM	RT	SN	SC	SH
103060	✓	CG0022	CG0022	NA,HW	NA,HW	NA,HW	NA,MI	NA,GH	NA,LS	NA,MW
103061	✓	CG0023	CG0023			JF	CL	RM	JN	NA,PV
103062	✓	CG0024	CG0024			NA,WH		LR	NA,MI	NA,TV
103063	✓	CG0025	CG0025					NA,TV		
103064	✓	CG0026	CG0026			NA,AG	NA,MW	NA,WH	NA,CC	NA,GH
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Fig. 3. Load balancing module integrated into clinical RIS PACS system and radiologist roster. Screenshot of work distribution module showing individually tailored reading lists. The system assigns different studies to radiologists based on rules such as subspecialty, relative value unit and patient type in order to balance the workload within a radiology department.

University of Singapore (NUS), Nanyang Technological University (NTU) and Agency for Science, Technology and Research (A*STAR), to build multidisciplinary research and development teams. Already, the Singapore AI technology community, with over 1000 scientists and students, is ranked second in the world by citation impact.[39-44] Key strengths include machine learning, deep learning, computer vision, robotics and natural language processing, all of which are essential for developing a core technology toolkit for medical imaging. There is also a vibrant entrepreneurial ecosystem with over 60 AI startups across the entire stack, providing a base of business and commercialisation know-how that can be adapted to radiology use cases.

Further, the Singapore healthcare ecosystem is well known for its strong digital infrastructure, centralised electronic medical record systems, and position as a trusted custodian of sensitive data, across public and private healthcare institutions alike. As such, there are compelling and immense opportunities for focused and structured research partnerships between Singapore clinical radiologists, AI technologists, entrepreneurs and healthcare providers alike to drive research and development for overcoming the challenges in AI for medical imaging applications.

Overcoming Challenges: Judicious Application of AI in Radiology

The first key challenge is in effectively leveraging the vast and rich troves of clinical imaging data that is latent in restructured hospital PACS for AI development research and development. Current AI methodologies require large volumes of high-quality artefact-free, datasets that are intensively annotated with ground truth labels for the learning tasks at hand. This introduces the need for careful extraction; matching across metadata fields and final diagnosis; as well as resource-intensive, clinically consistent labelling and image annotation. These curation and data preparation tasks occupy 50% to 70% of the time to develop AI prediction models, but are essential to ensure that the learned models are accurate, representative and generalisable for clinical use.

Recent works have explored partial automation of data curation tasks with preprocessing pipelines as well as the use of Natural Language Processing (NLP) to automatically derive image labels from radiology reports.[45,46] However, more careful efforts along these lines are urgently needed. Yet, it should also be noted that "ground truth labels" in clinical scenarios are often not straightforward, and patients can have many concurrent medical issues which may not be apparent from written medical records or radiology reports. For example, in interstitial lung disease, even a biopsy result is not necessarily a gold standard, as there can be sampling bias and histological mimics. Hence, the final diagnosis is often the result of a multidisciplinary review of each case with inputs from the primary respiratory physician, surgeon, radiologist and pathologist, which may not be apparent in the annotation process.

Furthermore, in complex cases, independent reads by different radiologists can lead to different assessments on ground truth labels (interobserver variability). To overcome these challenges, the technology research community is advancing deep learning approaches (e.g., by employing generative adversarial networks [GANs]) to learn from images in scenarios where clearly demarcated ground truth annotations are not available.[47-49] There is a need to rigorously evaluate the performance of such approaches across a range of medical imaging use cases to assess their applicability for clinical radiology tasks.

Radiologists need to work actively with relevant stakeholders to address the above challenges. First, there is a need to develop standards and tools to facilitate and encourage collaborative data use agreements,[50,51] and address important concerns around patient privacy and data security. Standards for de-identification, encryption and network access need to be developed. Researchers and institutions, mindful of the recent controversy over recent high-profile data leaks may be reluctant to share data without an assurance that the risks of compromise of data security have been adequately addressed. Second, there is a need for data integrity standards, grounded in rigorous evaluation of the different approaches for data curation as well as the degree and types of labelling and annotation required. For these efforts, a balance must be struck between realising potential research gains on the one hand, and the ethical protection of patients' autonomy and rights to privacy, and the responsibilities of clinical institutions to protect the data they contain, on the other.

The second key challenge lies in the translational process of integrating AI into existing hospital information and radiology systems, where they can be validated clinically and systemically. Non-trivial questions around whether AI models should reside inside PACS like any other analytical tool or in between image acquisition modality and PACS—presenting numerical opinions to the radiologist in form of a mini-report such as calcium scoring, bone age, myocardial tissue native relaxation properties and likelihood ratios need to be answered. These challenges present important opportunities for research and development.

It is critical to ensure that medical ethics are front and centre in any efforts to develop and translate AI for medical use. Included in the basic tenets of medical ethics are respect for autonomy, non-maleficence, beneficence, and justice, to work for the common good and benefit of humanity. These principles—familiar to all radiologists—will need to be hard-wired in the development or implementation of AI for clinical use. Although it ought to be self-evident that AI should not be given any autonomous power to deceive, harm, destroy, or diminish the rights of individual human beings or communities, it may not possible to programme such ethical principles directly, since the machine is equipped only with pauci-dimensional linguistic and logical-mathematical intelligence.[52,53] Thus, care should be taken to ensure the safe development and implementation of AI tools in clinical radiology. While AI is less subject to cognitive biases experienced by human operators, it is still vulnerable to non-apparent biases in the data and/or algorithm.[11] If an AI model is trained using incorrect, contaminated or biased data, it could subsequently make systematic errors. Radiologists will need to validate predictions made by AI models for false-negatives and false-positives.[54] This also poses a large but not insurmountable problem of the "black box" nature of AI systems, which requires a serious and focused effort by those engineering these systems to increase the transparency and explanability of the processes contained within diagnostic or predictive models.[55] Crucially, with life-critical investigations, AI interpretation should require mandatory supervision by a human expert "in-the-loop" in order to guarantee safety, accountability and legal liability, in this case, the radiologist.[56]

Systemic entry barriers for early innovations in digital health innovation need also to be addressed. A potential national initiative to address such barriers is through the Licensing Experimentation and Adaptation Programme (LEAP),[57] a sandbox environment that allows patients and caregivers to benefit from early access to new healthcare models, without the high costs associated with large scale implementation.[58] This can serve as a way to scale up sufficiently before widespread adoption and licensing under the Healthcare Services Act (HCSA), allowing a 'Fail Early, Fail Fast, Learn Cheaply' approach.[59]

The third key challenge lies in developing a framework for radiologists, AI technologists and stakeholders to work together to drive progress. The funding and resource allocations for AI are currently being developed, and recent initiatives by the Singapore government toward developing AI at a broad strategic level have created exciting possibilities for researchers. Launched in 2017, the AI SG initiative is backed by $150 mil funding from the National Research Foundation, and driven by partnerships across various government agencies.[60] Within the MOH, digital innovation to improve patient outcomes is being supported by the National Health Innovation Centre (NHIC), which provides translational funding and strategic guidance to accelerate healthcare innovation,[61] and the Integrated Health Information Systems (IHiS) Research and Innovation Enterprise Programme (RIEP), which launched its inaugural National HealthTech Challenge 2018 in March, attracting submissions from all healthcare clusters.[62] More recently, the first clinician-innovator award was introduced by the National Medical Research Council (NMRC) in June 2018.[63] Indeed, opportunities are available for Singapore radiologists to partner with strategic government initiatives for AI in healthcare, and work with research and commercial stakeholders (Fig. 4).

How do we balance protecting the patient's individual interests and at the same time make sure society as a whole, benefits? A sensible approach would be to assert that "if big data research of today is clinical practice tomorrow", then this research should be considered a core business of the Singapore restructured hospital system.[64] Early adopters must also be prepared to deal with any unintended consequences and failures (conspicuous or otherwise) arising from disruptive technology.[65] There is a great deal of private health information in imaging data, and we are obligated by data privacy laws and radiologists' foundational medical ethics, to be responsible stewards of the trust the public has placed in us.[66,67] Hence, a framework to address issues such as the risks of bad actors/hackers compromising AI systems is needed within the vocabulary of institutional review boards (IRBs) and as complementary amendments to the law such as the Human Biomedical Research Act (HBRA)[68] to ensure ethics, safety, and data protection.

The "Centaur" Paradigm and Augmented Radiology

One of the consequences of the made-for-mass-media events pitting human and machine, such as the famous chess match between world champion Garry Kasparov and IBM's Deep Blue, has been the creation of a new form of chess player. A "centaur" chess player (evoking the half-horse, half-human of Greek mythology) combines human creativity and the ability to understand opponents using empathy, with a computer's brute-force calculations and memory

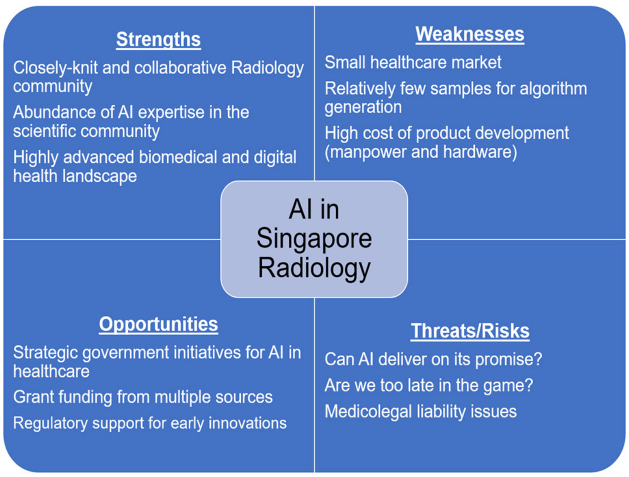

Fig 4. Strength, weakness, opportunity and threat (SWOT) analysis of AI in Singapore Radiology.

of almost all known chess moves and possible outcomes, to suggest a new paradigm of interconnectedness between humans and machines. Today, "centaur" chess players not only surpass grandmasters, but more importantly, also beat solo computers without humans. More recently, a cybersecurity system where people and machines worked together to detect cyber attacks was 3 times more accurate than the computer alone: machines outperformed humans at detecting unusual activity on the network, but humans were better at recognising which kinds of unusual activity were purely random and which were malicious.[69]

Similarly, the AI radiology systems being designed today are also human-computer "centaur" systems, and it is imperative to effectively leverage the respective strengths and roles of both.[70] The higher order metacognition, situational awareness, intuition, and creative thinking of humans can be augmented by appropriately designed smart machines to better facilitate complex pattern recognition as well as quantitative and probabilistic interpretation of clinical data to inform decision-making.[71,72] For example, a radiologist reading a complex oncology case with non-evident diagnosis or prognosis, may benefit from augmentation by semantic image retrieval and NLP tools that can automatically query the database for similar cases and display the overlaps and diagnostic/clinical outcomes for consideration. Smart tools may also have been helpful in previous disease outbreaks—clusters of individuals from different hospitals suffering magnetic resonance imaging (MRI)-detected hypoglycaemic brain damage from consumption of illicit medications could have been discovered earlier and more comprehensively if augmented by machine-learned data aggregation and pattern recognition, separating cases into typical and atypical.[73] A radiologist-in-the-loop, using smart narrow AI tools, may even be able to discern MRI lesion patterns that differentiate between 2 different types of brain infection (Nipah virus versus Japanese encephalitis), and make the mental leap to suggest pathogenesis in a novel infectious agent, even at the height of disease outbreak.[74]

Ancillary reporting tasks offer one example of a radiologist and machine augmenting one another to increase efficiency and accuracy. An AI with vision and NLP capabilities may learn from retrospective databases to present auto-complete options and fill-ins on the fly. This would augment the radiologist in writing their reports, who would then improve the AI by making corrections.

Conclusion

AI has tremendous potential to transform the practice of diagnostic radiology for the better, and play a pivotal role in Singapore's vision of patient-centric, value-added medical care that goes beyond healthcare to health. When the great diagnostician, Sir William Osler, declared that "Medicine is a science of uncertainty and an art of probability", he did so in the days when diagnosis depended mainly on clinical history and examination, not on an image. Living with uncertainty has been a fundamental patient experience of illness, and although medical images can provide an illusory visual representation of certainty, patient distress and suffering does not end when a diagnostic label is found. Today, as AI harnesses the full power of the probabilistic sciences, radiologists are poised on the cusp of a new revolution in the art of uncertainty. Building on the ethical, compassionate roots of good medical practice, AI can augment and refine the radiologist's human judgement in our constant pursuit of better care for our patients, and for humanity, because "the secret of the care of the patient, is in caring for the patient".[75,76]

Acknowledgement

The authors gratefully acknowledge Cheng Qianhui (National Neuroscience Institute Singapore) for her editorial assistance, and many colleagues for their input and advice.

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