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Review

# The future of radiology augmented with Artificial Intelligence: A strategy for success

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ABSTRACT

The rapid development of Artificial Intelligence/deep learning technology and its implementation into routine clinical imaging will cause a major transformation to the practice of radiology. Strategic positioning will ensure the successful transition of radiologists into their new roles as augmented clinicians. This paper describes an overall vision on how to achieve a smooth transition through the practice of augmented radiology where radiologists-in-the-loop ensure the safe implementation of Artificial Intelligence systems.

## 1. Background

Radiology is in need of a strategy to future-proof the profession. A diagnostic radiologist is a postgraduate subspecialty-trained medical doctor who is skilled in interpreting medical images such as Digital radiographs, CT scans, Ultrasounds, Nuclear Medicine studies and MRIs and using them to guide management of disease in patients. But recently, experts in Artificial Intelligence (AI) have warned that radiologists may soon be out of a job, one being none other than the grand master of deep learning himself, Geoffrey Hinton [1].

In some ways, Hinton may be right. Since 1895 when Wilhelm Roentgen first discovered ‘x-rays’ [2], nothing has come even remotely close to the disruption potential posed by Artificial Intelligence. It is a double-edged sword, which, if wielded expertly, will propel radiology and radiologists well into the next century. On the converse, the margin for complacency is narrow, and perils abound if radiologists choose to adopt a ‘wait-and-see’ approach and instead allow pure market forces to transform the industry.

A middle ground has to be achieved in the tug-of-war between a specialty whose aims has always been of a noble pursuit of cutting-edge technology put to good use in achieving the best possible care for patients, and a multi-billion-dollar imaging industry dominated by behemoths of the late, great industrial age, such as General Electric, IBM, Siemens, Samsung and Phillips [3].

The overall vision for this strategy is for the safe implementation of AI systems in radiology, where radiologists are mandatory as component human authorities, or simply put: ‘radiologist-in-the-loop’ systems. Professor David Autor described the ‘O-ring principle’ in his paper on the future of workplace automation: given a situation where a collection of tasks need to be done together to successfully accomplish a main task, if some of the tasks can be automated, the economic value of the human inputs for the other tasks that cannot be automated will increase [4,5]. For radiologists, examples of the most important tasks that cannot be automated would include leading multidisciplinary meetings and making judgement calls, along with the verification of reports. With automation, radiologists increase rather than decrease their value.

Machine learning in the form of image processing, computer vision and natural language processing are the key AI technologies forming the pillars of this new Augmented Radiology future. According to Porter's Generic Strategies model, there are three basic options available to organizations for gaining a competitive edge. These are: Cost Leadership, Differentiation and Focus [6]. Strategically, the use of Porter’s generic strategies to create a competitive advantage hinge upon the reduction of overall cost of imaging to the patient, by increasing the productivity of radiologists through the automation of time-consuming, low-value, mundane and repetitive tasks such as nodule-detection.

This automation also creates differentiation for radiology as a product, if it can be harnessed to deliver medical imaging which is more accurate, more convenient and safer than it is presently. Last, but not least, Augmented Radiology has the potential to form new niche areas for growth of the specialty, notably in radiogenomics, report data mining and research [7–9].

## 2. The current state of radiology and the need for a strategy

Radiologists are not unfamiliar with Artificial Intelligence, pioneering work in medical imaging perception in the 1980s [10]. We are

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domain experts in medical imaging, medical physics and radiation safety. But in the past 5–10 years, there have been substantial new innovations in imaging from deep learning methods of image classification. Current artificial neural networks have accuracy rates which surpass those of human radiologists in narrow-based tasks such as nodule detection [11,12].

The first step in formulating a strategy is defining our capabilities and identifying the competitive forces which pose a threat. We face competition from other medical specialties who spend more time interacting with patients and who may choose to purchase AI technologies. We also face competition from equipment vendors who manufacture imaging devices such as CT scanners.

Our greatest strength lies, counterintuitively, not in our ability to tap on experience to accurately detect or classify images of disease, but in our ability to make clinical judgements based on this data, and this is where we outshine diagnostic algorithms. Judgement is developed not only from knowledge gained from radiology practice but stems from many years of undergraduate medical training beforehand. Currently, radiologists differentiate ourselves by integrating multimodal streams of data, from electronic health records and discussions with other colleagues from different specialties. This is a very strong entry barrier.

AI technology in itself is a fundamental technology which should not be resisted e.g. by withholding domain expertise from software developers, on the contrary, our strategic goal should be to further differentiate ourselves by creating hybrid Radiologists and AI as a form of collective intelligence.

Apart from thinking of ourselves as a product, we can also position ourselves as buyers to exert a strategic force upon the market and by integrating backward. Software is much easier to create than machines, and deep learning models are already freely available as open source material online. Instead of buying expensive AI software, we have been creating our own, in house.

In the future, diversification of radiology into a broader field, utilizing all forms of data, including metadata (e.g. electronic health records), signals and biometrics to arrive at timely diagnosis around the clock is a probable strategy. Building an ecosystem to sustain this, together with other "information specialists" such as Pathologists [13,14], would create an even greater competitive advantage.

Psychologically, creating "brand identification" by connecting to our patients via community outreach, fostering awareness of our role in the healthcare team and by increasing face-to-face interactions would help to rebrand Radiologists augmented with AI as the new gold-standard in diagnosis.

## 3. General use cases, potential impact and implementation strategy

Broadly, several use cases should be targeted for implementation within the scope of radiology. They can be divided into task-based categories:

### *3.1. Detection and prediction automation*

Machine learning (ML) is poised to automate detection of lung nodules on CT scans [15] and pneumonia on chest x-rays, with early results published in non peer-reviewed online archives showing some promise [16]. The next step is to increase the ability of these ML systems to predict the behavior of pre-cancerous lesions on CT scans by regression or modelling, to reduce the number of unnecessary invasive tests such as biopsy. This has the greatest potential for use in population screening for cancer, e.g. lung cancer, especially in countries where there is a shortage of radiologists relative to the populations they serve.

### *3.2. Intelligence augmentation*

A buzzword replacing AI at the recent World Economic Forum was IA, or Intelligence Augmentation [17]. Combining AI and radiologists as a form of hybrid intelligence promises to achieve even higher levels of accuracy in diagnosis. A working paper by Nagar [18] showed that groups of human and AI agents working together make more accurate predictions compared to humans or AI alone. This observation may or may not hold true for radiological diagnosis and requires scientific validation and greater scrutiny with peer-reviewed studies. Perhaps even more crucially, having a radiologist-in-the-loop within these systems will help to ensure patient safety standards are met and creates judicial transparency, which allows legal liability to be assigned to the radiologist component human authority.

### *3.3. Precision diagnostics and big data*

Research in precision medicine will create a need for precision diagnostics. As we discover how gene expression is linked to imaging features of tumours, machine learning will be required to mine the huge trove of data derived from imaging to assess tumour genetics and behaviour, as well as response to treatment [7–9,19–21]. Apart from cancer, precision diagnostics will conceivably be applied to chronic and degenerative diseases such as Alzheimer's and coronary heart disease, or indeed any disease with genetic and imaging biomarker correlation.

### *3.4. Radiological decision support systems*

The number of imaging studies performed each year has skyrocketed over the last two decades, almost doubling every ten years [22,23]. Machine learning is already used in advanced driver assist systems on roads, increasing safety and reducing the number of accidents. Similarly, a form of 'driver-assist' or decision support can be applied to diagnostic imaging, which may be particularly valuable for studies performed after office hours, when radiologists are either unavailable or operating on a skeleton-crew. This reduces information overload and burnout amongst radiologists, who already interpret one image every 3–4 s [24]. These systems can also aid the rapid detection of emergency conditions such as stroke in neuroimaging, in which AI has been used to analyse non-enhanced CT images and MRI images to automatically detect infarcts, segment infarct volumes and even differentiate thrombus from plaque in carotid arteries on CT images [25,26]

## 4. Impact upon cost leadership, differentiation and focus

One of the most obvious strategies to drive radiology forward is cost leadership. The integration of machine learning in imaging diagnosis has the potential to cut costs for patients and insurance companies by half [27]. It may cost as little as $1000 USD to install machine learning enabled chips capable of processing 260 million images per day [28]. Put into perspective, that is more than the sum of all MRI and CT scans performed in the USA daily. A thousand dollars is the current cost to payer for a single MRI study in some countries, such as the USA.

Radiologists utilizing AI to diagnose disease, or Augmented Radiology, could be applied as a differentiation strategy especially if patients (buyers) perceive this as having value. Apart from creating value by increasing diagnostic accuracy, this form of hybrid intelligence may increase patient access to imaging especially in remote areas and provide round-the-clock services for routine studies, increasing convenience.

Finally, projecting far forward into the horizon, finding a niche for hybrid Augmented Radiologist systems is an important focus strategy which can synergistically increase the impact of the first two strategies. As alluded to earlier, there are many research and clinical applications in radiology which cannot progress without the aid of machine learning, particularly those which involve data-mining. This is true of molecular imaging, radiomics, radiogenomics and large population cancer screening.

## 5. Defining roles, technical considerations and requirements for implementation

The individuals involved in implementing these initiatives include the Chief Information Officer (CIO) of each hospital, radiology leadership in committees and academic bodies such as professional colleges and societies, as well as individual radiologists.

The CIO's role is to ensure that these initiatives can be implemented safely and effectively so that patient safety and privacy is not compromised, integration into existing electronic health data systems and alignment with the rest of the hospital's policy. If the hospital has a Chief Data Officer (CDO), their role will be to safeguard the use of data for validation and training of machine learning systems and other data governance issues [29].

Radiology committees from professional colleges and societies are tasked with creating frameworks and guidelines for the entire professional body. These frameworks define the steps required to advance and implement AI systems in radiology, as well as a general roadmap for the future. They may also set standards for the validation of these technologies. These committees aid government policy makers in drafting regulations regarding its safe use.

Individual radiologists will have to play a role in actively participating in the development process and integration of machine learning into their daily workflow. Most of this will come in the form of creating validated training datasets for machine learning models. They will also act as consultants to machine learning companies to develop new use-cases and perform beta testing for products.

Incorporation of machine learning technology will most likely become the driving force for business growth in healthcare in the future, and machine learning is aligned to the strategy of increasing the value of Radiology in healthcare, whilst lowering costs and creating momentum for progress in medical informatics.

Promising as it may be, current machine learning technology is still quite a few steps away from successful implementation into radiology. Most emerging technologies undergo a 'hype cycle' and fail to meet their promised potential during the phase of implementation, for example in 2013, augmented reality glasses were introduced but have since remained in niche usage, far from the mainstream adoption that was predicted during initial product launch. Considerations in the implementation phase will include integration of systems into current IT environments, electronic health records, picture archiving and communication system (PACS) and radiology information systems (RIS).

Technological considerations arise mainly in acquisition of hardware and improvements in connectivity bandwidth between hospitals and departments. Access to secure cloud platforms and data storage will be essential, if not indispensable. High quality microphones or even multiple microphones are required for adequate speech recognition [30,31] and if voice generative NLP is to be applied as a user interface between the NLP systems and patients, the generated voices would need to sound more human-like to alleviate patient anxiety and prevent patient rejection of the technology.

Vendors of platforms delivering AI solutions also face the significant hurdle of the continuous updating and upgrading of these systems as AI and imaging technologies improve, as well as keeping up-to-date with the latest scientific progress in radiology and medicine.

Capital investment for upgrading hospital infrastructure, mainly in data storage, connectivity bandwidth and computational hardware would be required. Further on, upskilling of IT support teams to be able to address helpdesk queries and troubleshoot issues is crucial.

## 6. Organizational aspects of implementation

The main people in charge of implementing these initiatives would be the hospital CIO and/or chief data officer, as well as the department chief at the line-managerial level. The hospital CIO's duties would include ensuring that the systems are able to integrate into existing IT infrastructure, and purchasing these systems and updates.

The chief of radiology's duty would be to ensure radiology staff are trained adequately to use these systems and that this new software would not pose a risk to patient safety by auditing error rates before and after implementation.

The utilization of AI is very much in line with the business strategy of "value-added radiology" or "Imaging 3.0" as espoused by the American College of Radiology [32], which is a set of initiatives to bring radiology to a leadership role in medicine and to catalyze a shift in radiology culture where care is delivered in a more patient-centered way: so instead of doing things "to" patients, radiologists will be able to do things "for" patients. AI will enable radiologists to spend face time with patients to educate, counsel and guide them in their imaging decisions.

## 7. Roadmap for the implementation of AI in radiology

A few key areas can be automated with AI in the near future with machine learning technologies which already exist:

1. Automated image segmentation, lesion detection, measurement, labelling and comparison with historical images. This technology has already been debuted on the commercial stage at the recent Radiological Society of North America (RSNA) annual meeting 2017 in Chicago.
2. Generating radiology reports: most radiology reports are written in prose rather than in lists, necessitating long hours of typing and dictation on the part of radiologists to craft these reports, which must be factually and grammatically accurate. Natural language processing (NLP) and Natural language generation would help reduce much of this by either improvement in current technology for speech recognition or by creating reports from images present on the scan. This is a much harder task which would involve amalgamation with image classification machine learning.
3. Semantic error detection in reports: NLP would help to 'understand' the body of the radiology report, and conceptualize what the radiologist is trying to convey to the clinical team. It would then be able to act as a second reader and warn the radiologist of semantic errors before a report is finalized and verified. In a study by Mayo clinic, it was found that 9.7% of speech recognition generated radiological reports contained errors, 1.9% of these were considered material [33].
4. Data mining for research: a rich treasure trove of data resides in historical radiological reports which are stored in electronic health record databases across the globe. This data could be mined with NLP to create searchable databases classified by types of disease entities, concepts, keywords and sentiments. Each datapoint could then be combined in multiple permutations to answer research hypotheses, automating medical research which is painstakingly slow and prone to data input errors.
5. Business Intelligence for radiologists: machine learning has the potential to vastly improve business intelligence systems that allow real-time dash-boarding and alert systems, workflow analysis and improvement, outcomes measures and performance assessment. This in turn increases the throughput and efficacy of radiology practices and presumably improves patient satisfaction through shorter waiting times.

Several other potential use-cases for radiology require further advancement in AI technology from what is available today, and may be reserved for longer timelines in implementation. These include automated population screening and automated patient triage systems in emergency departments.

Other AI and radiology combinatorial fields such as radiomics and radiogenomics are in their nascent stage of development and sit on timelines which stretch into the more distant future. In addition to greater technological hurdles to achieving these initiatives, these also have greater potential for job displacement (but not necessarily job *replacement*), and necessitate more detailed planning and ethical discussion before implementation.

## 8. Special considerations, job displacement and risk mitigation

Healthcare is one of the more lucrative business opportunities within most economies worldwide, perhaps even more so in developing nations with growing middle classes who can afford self-funded healthcare. Not surprisingly, medical imaging computing is the most published subject in the scientific literature amongst uses of deep learning in healthcare [34]. What this means is that it is likely, although not yet confirmed, that radiology will be the first medical specialty to be disrupted in the field.

For all that has been said about AI augmenting radiologists and making the task of diagnosis more efficient and accurate, we should also be prepared for the likely scenario where the productivity gains from employing these solutions would lead to reduction in manpower requirements due to less time spent on traditional radiological tasks such as nodule detection and measurement.

The way to mitigate these risks would be to create new jobs or roles within the healthcare sphere to employ people displaced by these technologies. One good example of a replacement job would be medical data scientist, which could be taken up by radiology residents who are open to an early-career switch or role expansion. Societal norms dictate that some form of social and financial support or reimbursement should be provided to reduce the friction of transitioning into these new jobs, which could come in the form of upskilling cash rebates, educational bursaries and scholarships. These transitions should ideally take place as early in a doctor's career as possible to minimize personal and psychological impact upon the individual.

Most radiologists would agree that a major concern is the definition of tasks which should be automated and those which should remain radiologist-only tasks, with the overarching principle of safeguarding patient safety and data privacy. The hypothesis that Human and AI hybrid intelligence outperforms human or AI standalone intelligence has held true in early medical imaging computing research, at least for the time being. A recent press release from a startup AI company found that their radiology decision support system could achieve greater accuracy for bone fracture detection than radiologists alone and many times better than traditional computer vision approaches [35].

Regulatory policy would play a critical role in determining the outcome of this division of labor. It is expected that both scientific evidence and policies will align to mandate human-in-the-loop systems where radiologists provide the final verification of diagnosis, either by way of AI decision support or standalone human judgement relying on AI for lesion detection, labelling and feature classification (the former more likely in emergency settings with a need for expedited results). Either way, the common thread is that human judgement will remain a radiologist's domain, with varying degrees of AI automation of repetitive and mundane tasks.

## 9. Safety, privacy, moral and ethical concerns

These remain a large shadow looming over the implementation of AI in healthcare. Notwithstanding these concerns, recent signals from the US FDA portend that governments are keen to support AI technology adoption in the healthcare domain [36]. Borrowing from the Asilomar AI principles [37], the key ethical concerns for imaging AI are:

1. Safety: this is a key imperative for medical AI systems which would be inextricably involved in safeguarding the health of sick individuals at their most vulnerable state. Medical ethics imposes stringent ethical standards upon physicians to protect patient safety by the principle of non-maleficence, dictating that any doctor must 'first, do no harm'. The primacy of this principle translates into a requirement that any AI system must be validated to be safe, accurate and infallible before it can be used on patients.
2. Failure and Judicial Transparency: If an AI system were to fail or cause harm, it should be possible to determine why, and if the system were involved in judgement-making, there should be ways to explain satisfactorily the process involved in arriving at the decision and this should be auditable by a human-in-the-loop (a component human authority), during the process of arriving at the decision. This enables legal liability to be assigned to a human authority, and for the radiologist to assume responsibility for the action.
3. Privacy: most AI systems would have access to protected health information (PHI) either on-site or in cloud-based storage and therefore pose risks to patient privacy. A way to mitigate these concerns would be through law reform to insert complementary amendments into existing PHI legislation. AI system designers should ensure that algorithms be granted access only to relevant PHI (need-to-know basis). Collection of PHI data by third-party AI companies should be audited by relevant authorities to protect data usage and to ensure compliance within the framework of patient consent.

## 10. Global radiology impact and global RADIOLOGISTS' response

The impact of AI is beginning to send ripples throughout the international radiology community, dominating industry and academic headlines, as well as becoming sellout 'standing-room only' sessions at international radiology meetings. The impact in reading rooms has been more muted, with relatively few departments in academic centers and research institutes being involved in AI research and user acceptance testing. Notably, many efforts have focused on industry and regulation but more is required in educating the young generation of digital natives who will become our next generation of radiologists or Data scientists. Recently at the European Congress of Radiology (ECR) 2018 meeting in Vienna the subject of leveraging diversity and unity as one body of radiologists was highlighted as a strategic strength. Not all radiology communities have formed workgroups to generate roadmaps for the guided progress of AI in radiology, but for countries and regions which have done so, e.g. USA, UK, Europe, and in Asia, Singapore, frameworks for regulatory policy, quality assurance and forming partnerships with industry are recurring themes. Perhaps forming global partnerships for a united radiological body or set of principles would help galvanise the fraternity further in preparation for what lies ahead.

## 11. Conclusion

According to Porter's Generic Strategies model, Cost Leadership, Differentiation and Focus can be used to create a competitive advantage. The roadmap for the future of AI augmented Radiology is guided by the direction provided by these strategies: reduction of overall cost of imaging to the patient/payer by increasing the productivity of radiologists through the automation of time-consuming and low cognitive value tasks and by differentiating Augmented Radiology as the cornerstone of precision medicine which delivers imaging results which are safer, more accurate and more conveniently than at present. Augmented Radiology also has the potential to foster new niche areas for growth, notably in radiomics, radiogenomics, data mining and research. Finally, Augmented Radiology increases the value of radiologists, economically, as well as socially: to our patients, and to the multidisciplinary healthcare team.

## Declarations of interest

None.

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