peer reviewed **ARTICLE OF INTEREST**

Moving towards automated digitised image interpretation. Friend or foe?

Riaan van de Venter *N Dip Rad (D), BTech: Rad (D), MTech: Rad (Research); TEFL Cert; PDTE*

Nelson Mandela University, Port Elizabeth, South Africa

Abstract

Radiology and radiography have always been at the forefront of rapid technological advancements, requiring flexibility to adapt to different workflow approaches and systems in a short time span. This is no different with the near-reality of the introduction of artificial intelligence (AI), in radiology. Artificial intelligence is automating pattern recognition and image interpretation currently done by humans, and providing a digitised interpretation to the observer. It is not going to replace the knowledge and/or expertise of radiologists or radiographers who still need to analyse and interpret radiographic images. Instead, AI fulfils a supporting function to assist in enhancing accuracy of image interpretation and pattern recognition to ultimately improve patient outcomes. However, the full extent of implications for practice is not yet fully explored; many challenges still require attention and deliberation.

Keywords artificial intelligence, deep learning algorithms, machine learning, enhanced patient outcomes, support, digitised pattern recognition, ethico-legal implications

Introduction

Currently trending in healthcare and radiology, is artificial intelligence (AI) and its role in image interpretation; a topic that dominated the 2017 Radiological Society of North America (RSNA) conference. Computer-based face recognition systems, Uber, the automatic pilot in an aircraft, and the Google translator, as examples, are all various forms of AI; more specifically machine learning (ML). Even driverless cars use AI to recognise when to stop at robots (traffic lights). AI involves a category of computer-based techniques that perform problem-solving and reasoning tasks, as well as tasks such as speech recognition, visual perception and decision-making.[1-2] Transferring this to image interpretation in radiology, AI can be likened to an automated digitised programmed pattern recognition method, since AI gets programmed to perform tasks once only considered characteristic of human beings.

Image interpretation is heavily influenced by visual perception, which introduces errors in perceptual, and subsequent analytic errors, on the part of an observer.[3] Considering alternative methods to reduce human error, associated with image interpretation and pattern recognition, and the subsequent number of misdiagnoses, has been debated since 1948. Tuddendam and Giger both argued that a possible way forward is computer-based, automated pattern recognition and diagnostic systems.[4] Computer-aided diagnosis (CAD) software programmes are already used in mammography,[5] and computed tomography colonography (CTC). However, CAD brings about increased interpretation times and an increase in false positive rates (i.e. incorrectly identifying that a lesion is present), but it has great sensitivity,[5-6] which therefore still requires human intervention regarding a final holistic interpretation and diagnosis. The current endeavour of AI, with regard to image interpretation and pattern recognition, is to improve on the limitations of CAD without displacing, by implication, the need for the expertise of radiologists and trained radiographers to provide a comprehensive overall interpretation of the examination.

The image perceived by an observer is formed by a complex interaction and interconnection between the image viewed, the optical system of the human eye, and the neural circuitry connected to the retina, which enables an image to be formed of the light stimuli observed and perceived to make sense of the stimuli; this is how pattern recognition starts.[7] Patterns entail repetition in a particular sequence; this implies some sort of organisation. Therefore, there is some sort of relationship between the various elements. The human eye is great at recognising patterns and distinguishing which elements relate to one another. This ability is however not natural, but instead a skill learnt.[5] Considering the radiology context, to make a diagnosis requires a critical analysis of radiographic images. This evaluation is underpinned by knowledge gained through intensive formal and informal learning and training which enable radiologists, and radiographers, to recognise particular radiographic signs and appearances related to a particular pathological and physiological process. This is done to determine that an abnormality or condition is either present or absent.

Of note is that one's confidence regarding pattern recognition and image interpretation also increases with experience and practice by viewing many images of an anatomical region in order to recognise patterns and associated variations. In other words, human beings process visual data to recognise similar patterns in order to associate them with a specific abnormality, normal variant or condition. Understanding, and having a knowledge of this humanistic perspective to image interpretation, and pattern recognition enables our understanding of AI and the role it will fulfil. The principles apply to AI too because many datasets of a specific examination, for example adult wrist images, are required to correctly interpret patterns.

It can therefore be argued that AI will act as a support structure and not a replacement of human interpreters. It will be used to alleviate current practice constraint pertaining to human resources and timely reporting of radiographic images. AI should therefore be embraced as a friend and not fended off as a foe.

This paper aims to provide readers with a brief introduction to AI and its implication for radiological and radiographic practice. Terminology associated with AI sets the tone for the overview of AI. This is followed by a synopsis of how image interpretation is achieved by means of AI and the potential practice implications contrasted with research findings, opinions and current practices. Full details of the architectural intricacies involved in the realm of computer sciences related to deep-learning convolutional neural networks are beyond the scope of this paper, as it aims to provide an introductory understanding on AI and ML.

Terminology associated with artificial intelligence algorithms used in image interpretation

As with all technological advances in imaging and medicine, we need to be familiar with the language of AI's concepts.

• ***Algorithm***

An algorithm can be defined as a set of specific rules or mathematical instructions, with a predetermined number of action steps, used in computer science, to solve a particular problem. Algorithms form the basis for developing computer programmes.[8-9]

• ***Machine learning***

Machine learning (ML) is seen as a subcategory of AI that concentrates on programming. It allows a computer to formulate a specific model of the world; as new data are encountered this model can be modified.[1] ML is further subdivided into supervised and unsupervised learning. Supervised learning refers to training a programme by using a series of cases and diagnoses to make an automated prediction of the diagnosis of a new dataset, without providing the diagnosis. In contrast, unsupervised learning is when a programme takes a dataset and develops a model on its own without training.[1]

• ***Deep-learning convolutional neural network algorithm***

Deep learning involves the learning of multiple levels of representations, and abstractions to make meaning of the content of datasets of images, audio and texts, for example.[10] Convolutional neural networks (CNNs) are feedforward networks, with the ability of characteristic learning, containing multiple hidden layers, and which are considered an efficient recognition algorithm, widely used in image processing and pattern recognition.[10] The architecture of CNNs also enables fast training of these neural networks, which facilitates the deep learning process of multi-layered networks that are good at classifying images.[11]

• ***Encryption of data***

Encryption of data involves conversion of data into a secret code, which requires a secret key or password to enable one to read the encrypted file, and to get access to the content. Encryption of data is one of the most effective methods to accomplish data security.[12]

• ***Radiomics***

Radiomics extracts volumes of interest from large data sets of radiographic images and provides statistical data of an image. These are combined with other image data, such as clinical and genomic information, to provide a decision supporting tool for precision medicine for the most appropriate treatment at the correct time. This is especially applicable in oncology, where this quantified data could act as biomarkers to identify a tumour-type. Radiomics further has the potential to assist in diagnosing a disease by uncovering characteristics of the disease present that are not visible to the naked eye, which can provide and build predictive and prognostic assessments on the state of a disease process.[13]

Image interpretation and related processes in the context of artificial intelligence

Using deep-learning CNNs' algorithms, a programme is provided with a sample: preferably a large sample of radiographic images related to a specific pathological process or disease. The sample also generally contains variants of the same process/disease. The computer-based programme then uses the dataset to train itself in a self-taught method to recognise the various signals from the dataset related to the specific pathological process or disease. This information is then used to build a particular model: the primary aim of ML. When a new data set is encountered by this model developed by the initial data, the model can then provide a possible diagnosis on this new provided dataset.[14-15]

Of note, these deep-learning CNNs are specifically trained to diagnose and recognise patterns characteristic of a single and related pathological process or disease. For example, an algorithm developed to determine bone age will not be able to provide any predictive diagnostic information for a radiographic image of a cerebral haemorrhage. The developed algorithms also undergo rigorous experimental design, real-life application, and validation processes to ensure they are fit for purpose.[16] The deep-learning CNNs mimic visual perception, the neural network, and retina of the human eye, to make meaning of the content of the radiographic image which then leads to subsequent analysis of the image. These algorithms are able to perform tasks, of note, relating to image division, image registration, image fusion, image annotation, CAD and prognosis, and lesion detection, amongst others.[15-16]

Deep-learning CNN algorithms have been developed and have demonstrated promise in stratifying lung nodule risk,[16] converting positron emission tomography (PET) scans to magnetic resonance (MR) images,[17] improving accuracy of diagnosis and enhancing patient outcomes. Of note are specific abnormalities detected on a chest radiograph;[18] determining bone age from a hand radiographic image;[19] analysing renal biopsy images;[20] and predicting deaf paediatric patients' capacity to learning language.[21] These results demonstrate the powerful and beneficial role that AI can fulfil in the field of radiology and radiography. In addition, deep-learning algorithms also have demonstrated the capability to comprehend free-text radiology reports.[22]

The above findings of some studies underscore that AI/ machine learning has implications for future practice in the workplace. And this is no different for Africa, as Ghana has very recently rolled out the CAD4TB software programme to assist in early tuberculosis (TB) detection before sending patients for more expensive testing, such as the GeneXpert test. The CAD4TB also makes use of a deep learning technology to determine the likelihood of TB being present and can scan approximately 200 radiographic images daily.[23]

Implications for practice

As radiological technology advances and undergoes metamorphoses, so does the associated workflow and workload. Using computed tomography (CT) or MRI modalities as examples, a large amount of data are generated requiring critical evaluation by radiologists to make a diagnosis. To aid in streamlining the workflow many processing techniques are used; automatic analysis software assists radiologists to prioritise work, to multitask, and to keep adequate records of what is done and what still requires attention.[24]

AI holds similar benefits in store in the clinical environment. Given the extensive use of CT, and MRI, it is a reality that radiologists, worldwide, wade through numerous images on a daily basis. This is what underpinned the majority papers presented at the 2017 RSNA. Using these deep-learning algorithms, ML can assist in diagnostic and prognostic accuracy. Since radiomics and continuous updating and relearning of the algorithms, which will most probably happen frequently, could ensure that the most recent reference standards are used to interpret radiographic images. Literature demonstrates that algorithms can perform at a similar or a greater level of accuracy compared to a radiologist.[25-26] By implication, this leads to potential enhancement of patient outcomes, and shorter turnaround time for reporting of images. In addition, given the global shortage of radiologists to report on images, and the current UK practice enabling adequately trained radiographers to report on radiographic images,[27] AI could be integral to provide provisional or primary reports on radiographic images not routinely reported on or where an immediate report may not be possible. Further, AI-driven image interpretation could be used, depending on the organisational culture and practices adopted, as a first or second reader which a radiologist or radiographer could use to aid in the final diagnosis made. As previously explained radiomics can detect disease characteristics not visible to the naked eye. Therefore, AI should be seen as fulfilling a supporting function in the practice of image interpretation and pattern recognition.

Having access to these algorithms will significantly impact on workflow approaches and may require adopting new approaches. This will impact on service delivery to patients and clients. Radiomics may provide the possibility of more personalised care to patients. In addition, the continuous and infinite possibility of relearning algorithms, to keep them updated with the latest reference standards and variants of the particular pathological process and/or disease they are programmed to diagnose and recognise, could contribute to a reduction in missed lesion detection. Radiologists, and interpreting radiographers, could further redistribute their time spent on various tasks, as AI could take over the mundane and tedious tasks; clinical time could be shifted to engage in more intricate and complex tasks related to image interpretation.

However, the benefits of AI, and the relative novelty of deep-learning CNNs algorithms' use related to image interpretation are not without challenges. These include ethico-legal questions related to finances, sustainability, and data security. South Africa, and the rest of the world have specific legal frameworks governing the distribution of data, be it manually or digitally. These frameworks need to be adhered to. One effective way to secure patient data is encryption, but with the amount of hacking of big digital databases fairly recently, as presented in the news, ensuring data security does pose a potential big challenge that will require attention before AI is ultimately implemented.

As with any new technology, there will be competition among vendors and manufacturers. This competition brings about financial implications, and at the epicentre of this are patients. Utilising this service in radiology may turn out to increase the cost of services provided to patients/clients to make the service financially viable to the practice. This situation brings about the ethical question pertaining to the principle of justice and resource allocation. It furthermore poses a concern of whether this method will be sustainable in the long run; regulation in this realm also needs to be looked into in terms of standardisation of algorithm parameters and expectations, as well as validation and performance measurement.

Another challenge to be investigated would be vendor neutrality of the algorithms since they get programmed and modelled for very specific purposes. A hospital or imaging practice may not necessarily get all the necessary algorithms from a single vendor that suit their needs. So, one can easily see how this could become a very lucrative market, making healthcare transactional in a sense, which therefore defeats the purpose that AI has in mind to improve patient outcomes in the end.

Another challenge that may exist is obtaining substantial data to train an algorithm to detect a specific condition and associated variants, for which the algorithm has been developed. This challenge may be brought about by the unwillingness of institutions to share data with one another, leading to 'institutional xenophobia', and one could potentially understand this due to the competition existing in the market amongst vendors to develop unique algorithms.[28]

Therefore, Chang[29] rightfully points out that these initial stages to realising AI as common practice should be utilised to one's advantage to ensure that infrastructure and datasets, needed for initial training of deep-learning algorithms, should be invested in. AI should not be seen as a crisis although it is disruptive, like any change process; even PACS did this. However, those in radiology and radiography are more flexible to adopt to change than they think they are. With AI and deep learning this will be no different. The main challenge is that adoption of this technology will happen long before it can be implemented and consumed.[29]

The incorporation of AI and deep-learning, as common practice, will require learning a new technology, adapting to practice changes brought about by this, and then to adopt these practices as common everyday ones.

Conclusion

AI and deep-learning will not, in the current context, replace the need for the humanistic arm to healthcare, as well as in radiology; machines cannot necessarily provide the therapeutic care that a human's simple touch or listening ear can. Similarly, expert knowledge will not be replaced by AI and deep-learning pertaining to image interpretation and pattern recognition. Instead, it will assist in enhancing diagnostic accuracy, optimise workflow, and facilitate the process of greater patient-centred and personalised patient care. Deep-learning CNNs algorithms, as a subcategory of ML, operate similar to a human interpreter of radiographic images, and they are therefore nothing more than an automated, digitised programmed and learnt method of pattern recognition and image interpretation.

The findings of a healthcare market research survey conducted in the United States of America in December 2017 predict that by 2020, AI (or machine learning) technology will be used by most hospitals and imaging centres.[30] Three in four of the 133 respondents stated they use AI for breast imaging, one in four use it for lung imaging, and 19% for cardiovascular imaging. Other uses include pulmonary hypertension imaging, and neural aneurysmal imaging.[30]

The burning question is: Will AI in the near future be included in radiography curricula in South Africa? Hopefully future radiographic congresses will include papers on AI to start creating the awareness and educating the audiences about this emerging trend in image interpretation.

Therefore, by being proactive in educating oneself and keeping abreast of the latest trends in the profession, such as AI, one could embrace AI as a friend, opposed to an enemy.

Competing interests

No financial or personal relationships have inappropriately influenced the writing of this article.

References

1. Cross N. A primer on machine learning. ACR Bulletin, January 2017. [cited 2018 January 9]. Available from: https://acrbulletin.org/acr-bulletin-january-2017/1017-about-machine-learning
2. Merriam-Webster Dictionary. Artificial intelligence, January 2018. [cited 2018 February 4]. Available from: https://www.merriam-webster.com/dictionary/artificial%20intelligence
3. Alexander K. Reducing error in radiographic interpretation. Canadian Veterinary Journal, 2010; 51:533-536.
4. Kundel HL. History of research in medical image perception. J of American College of Radiologists, 2006; 3:402-408.
5. Tchou PM, Haygood TM, Atkinson EN, Stephens TW, Davis PL, Arribas EM, Geiser WR, Whitman GJ. Interpretation time of computer-aided detection at screening mammography. Radiology, 2010; 257 (1): 40 -46. Available from: http://pubs.rsna.org/doi/pdf/10.1148/radiol.10092170
6. Yee J. Virtual colonoscopy. Philadelphia: Wolters Kluwer, 2008, pages 209-218.
7. McConnell J, Eyres R, Nightingale J. Interpreting trauma radiographs. Oxford: Blackwell Publishing, 2005, pages 49-50.
8. Cambridge Dictionary. Algorithm. [cited 2018 February 4]. Available from: https://dictionary.cambridge.org/dictionary/english/algorithm
9. Dictionary.com. Algorithm. [cited 2018 February 4]. Available from: http://www.dictionary.com/browse/algorithm
10. Liu T, Fang S, Zhao Y, Wang P, Zhang J. Implementation of training convolutional neural networks, 2015. [cited 2018 February 4]. Available from: https://arxiv.org/ftp/arxiv/papers/1506/1506.01195.pdf
11. Nielsen MA. Neural networks and deep learning, 2017. [cited 2018 February 4]. Available from: http://neuralnetworksanddeeplearning.com/chap6.html
12. Beal V. Encryption, 2018. [cited 2018 February 4]. Available from: https://www.webopedia.com/TERM/E/encryption.html
13. Gillies RJ, Kinahan PE, Kricak H. Radiomics: Images are more than pictures, they are data. Radiology, 2016; 278 (2):563-577. Available from: http://pubs.rsna.org/doi/pdf/10.1148/radiol.2015151169
14. Artificial intelligence in health care: within touching distance. The Lancet, 2017; 390 (10114):2739. [cited 2018 January 31] Available from: http://www.thelancet.com/journals/lancet/article/PIIS0140-6736(17)31540-4/fulltext
15. Shen D, Wu G, Suk H. Deep learning in medical image analysis. Annual Review of Biomedical Engineering, 2017; 19:221-248. [cited 2018 February 4]. Available from: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5479722/
16. Ridley EL. Deep-learning algorithm can stratify lung nodule risk. November 2017. [cited 2017 December 15]. Available from: http://www.auntminnie.com/index.aspx?sec=rca&sub=rsna_2017&pag=dis&itemId=119166
17. Pearson D. AI technique turns PET scans into MR images. December 2017. [cited 2018 February 05]. Available from: http://www.healthimaging.com/topics/advanced-visualization/ai-technique-turns-pet-scans-mr-images
18. Ridley EL. Is seeing believing in imaging artificial intelligence? 8 December, 2017. [cited 2017 December 15]. Available from: http://www.auntminnie.com/index.aspx?sec=ser&sub=def&pag=dis&ItemID=119347
19. Pearson D. AI accurately tells children's age from hand x-rays. 3 November 2017. [cited 2018 February 1]. Available from: http://www.healthimaging.com/topics/imaging-informatics/ai-accurately-tells-children%E2%80%99s-age-hand-x-rays
20. O'Connor M. AI proves capable in analysing kidney biopsy images. 17 January 2018 [cited 2018 February 1]. Available from: http://www.healthimaging.com/topics/artificial-intelligence/ai-proves-capable-analyzing-kidney-biopsy-images
21. Rohman M. Brain MRI, AI predict deaf children's capacity to learn language. 16 January 2018. [cited 2018 February 1]. Available from: http://www.healthimaging.com/topics/molecular-imaging/neuroimaging/brain-mri-artificial-intelligence-predicts-deaf-children-s-capacity-learn-language
22. Pearson D. Deep-learning classifier understands free-text radiology reports. 15 November 2017. [cited 2018 February 1]. Available from: http://www.healthimaging.com/topics/imaging-informatics/deep-learning-classifier-understands-free-text-radiology-reports
23. Lahiaje E. Largest African e-health project in Ghana completed. 23 March 2018. [cited 2018 April 3]. Available from: http://mobile.ghanaweb.com/GhanaHomePage/health/Largest-African-e-health-project-in-Ghana-completed-637161
24. Cusack R, Vicente-Grabovetsky A, Mitchell DJ, Wild CJ, Auer T, Linke AC, Peelle JE. Automatic analysis (aa): efficient neuroimaging workflows and parallel processing using Matlab and XML. Front Neuroinform, 2015; 8 (article 90): 1-13. Available from: https://www.ncbi.nlm.nih.gov/pubmed/25642185
25. Yee KM. AI algorithm matches radiologists in breast screening exams. 12 December 2017. [cited 2018 February 1]. Available from: http://www.auntminnie.com/index.aspx?sec=ser&sub=def&pag=dis&ItemID=119385
26. Kubota T. Stanford algorithm can diagnose pneumonia better than radiologists. 15 November 2017. [cited 2018 February 1]. Available from: https://news.stanford.edu/2017/11/15/algorithm-outperforms-radiologists-diagnosing-pneumonia/
27. Snaith B, Hardy M, Lewis EF. Radiographer reporting in the UK: a longitudinal analysis. Radiography 2015: 24 (2):119-123. https://doi.org/10.1016/j.radi.2014.10.001
28. Rohman, M. AI and machine learning in radiology: 4 things to know. 5 February 2018. [cited 2018 February 6]. Available from: http://www.healthimaging.com/topics/artificial-intelligence/ai-and-machine-learning-radiology-4-things-know
29. Chang P: 3 things to know about AI, deep learning in 2018. 30 January 2018. [cited 2018 February 8]. Available from: http://www.healthimaging.com/topics/artificial-intelligence/3-things-know-about-ai-and-deep-learning-2018
30. Roham M. More hospitals than imaging centers are adopting AI, new report says. 6 February 2018. [cited 2018 February 11]. Available from: http://www.healthimaging.com/topics/artificial-intelligence/more-hospitals-imaging-centers-are-adopting-ai-new-report-says