Deep Learning in Radiology:
A Critical Analysis of Geoffrey Hinton's Vision

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1. CONTEXT: INTRODUCTION

The emerging influence of deep learning within the AI revolution has affected procedures in medicine and clinical practice, with the development of AI models in medical imaging and radiotherapy posing questions surrounding the need for radiologists in the near future.

Geoffrey Hinton, a prominent computer scientist and deep learning expert famously said in 2016: "We should stop training radiologists now. It's just completely obvious that within five years, deep learning is going to do better than radiologists. Any old problem where you have to predict something and you have a lot of data, deep learning is probably going to make it work better than the existing techniques".

Hinton's statement about the potential of deep learning in radiology sparked considerable debate across the fields of AI and healthcare. Since 2016, deep learning has made significant advancements which are being increasingly integrated into radiological practice, yet the complete replacement and hence redundancy of radiologists and the profession's respective training has not occurred.

Radiology is a branch of medicine that uses imaging techniques to diagnose diseases within a patient. This subdivides into a variety of imaging techniques such as X-rays, ultrasound, CT, PET, MRI etc. These imaging modalities provide detailed images of internal structures of the body without invasive procedures, playing a crucial role in detecting conditions such as cancer, heart disease and other internal injuries.

Radiology is broadly categorised into diagnostic radiology and interventional radiology. The former focuses on the use of imaging techniques to diagnose diseases, whereas the latter uses such image analysis to guide minimally invasive surgical procedures, such as biopsies, draining fluids or inserting catheters [1]. The common direction for this debate focuses on the diagnosis, however I argue that it is paramount to maintain a distinction for the role of AI between diagnostic and interventional radiology. I maintain that deep learning can significantly improve the detection and diagnosis of diseases in the short term, however will not be able to replace the medical precision required for interventional radiological practice anytime soon. Another important consideration involves using AI to improving medical education of both diagnostic and interventional radiology, offering more realistic simulation scenarios which are continuously updated on the latest medical information.

2. RATIONALE: CURRENT CHALLENGES IN RADIOLOGY

Advancements in medical imaging technology have led to a surge in both the volume and complexity of images for radiologists to interpret. Keeping up with these rapid developments and new diagnostic techniques is challenging, requiring radiologists to constantly update their knowledge for accurate and consistent image interpretation. Any variability in diagnoses among radiologists can negatively impact patient health and medical resource allocation.

A study in the Journal of the American Medical Association (JAMA) found significant variability (at least 40%) in radiologists' interpretations of mammograms [2], leading to potential underdiagnosis or overdiagnosis of breast cancer depending on the sensitivity of radiologists, resulting in either delayed treatment or unnecessary biopsies and patient anxiety.

Machine learning can enhance the accuracy, speed, and consistency of medical image analysis in radiology, reducing human error. It also supports personalised medicine by adapting to individual differences, for example how lung nodules in CT scans can present differently depending on patient factors such as age and smoking history, highlighting AI's role in standardising and interpreting diverse appearances of the same pathology.

Another challenge lies in radiology training itself, where AI can complement existing interactive learning for trainee radiologists. This 'bottom-up' [3] method, favored over traditional 'top-down' learning [4], faces challenges in preparation due to a shortage of patient cases or current simulations, especially for rarer radiological features and conditions.

Whilst one could argue, like Hinton, that improving radiology training via AI is meaningless if radiologists should be replaced altogether, I maintain that AI still has a significant role in radiology education, especially for interventional radiology which is harder to replace. AI can standardise training, improving diagnostic accuracy and consistency, perhaps then will radiologists be recognised. This approach also navigates the ethical issues of AI as a replacement, offering a less intrusive way to enhance radiological practices.

3. ARGUMENTATION: DISCUSSING G. HINTON'S STATEMENT

Hinton argues that deep learning should already be better than radiologists. The primary criterion for AI to be 'better' would most likely be a test performance metric such as accuracy or even sensitivity as this is within a medical context where typically false negatives have a larger negative impact than false positives. However one can also consider the speed and consistency improvements which AI offers, helping to improve global healthcare standardisation and allowing radiologists to focus on more complex cases. For example, a study from Stanford University created CheXNet [5], a 121-layer convolutional neural network, detecting diseases for example pneumonia on chest x-rays with a higher F1 metric than radiologists of varying years of experience.

Hinton's view on AI in radiology is reinforced by the global shortage of radiologists, with significant variations across regions. In countries with limited healthcare infrastructure, AI solutions like Zebra Medical Vision's [6] diagnostic tool provide a cost-effective and quicker alternative to traditional radiologist training, for example their work in countries such as Mexico. Even in well-resourced areas like the UK, where the NHS has only 8.5 radiologists per 100,000 people compared to Europe's average of 13 [7], AI can address the gap caused by lengthy medical training and the decreasing appeal of radiology due to AI replacement fears.

Contrarily, I believe Hinton misses the counterpart to diagnostic radiology, being interventional radiology (IR) which utilises medical imaging to guide smaller surgical procedures. Deep learning may enhance or substitute initial diagnostics in interventional radiology (IR), but replacing surgical procedures is unlikely in the near future due to the current limitations of healthcare robotics compared to the precision of trained interventional radiologists. Of course, Hinton focuses on deep learning as a solution for (presumably) diagnostic radiology only, however to 'stop training radiologists' altogether is an extreme assertion which fails to consider IR. Perhaps Hinton would suggest surgeons carry out the surgical procedures, instead of radiologists, however I argue that the same clinician perform AI-assisted image analysis followed by the interventional steps, especially since a radiologist's role extends to specific medical domain knowledge and not just image analysis.

Additionally, medical datasets typically suffer from class imbalance, with a heavy skew towards the negative (no disease) class. This could result in models having poor sensitivity to particularly rare conditions, where data is significantly lacking. Even with resampling techniques such as SMOTE, or ensemble methods which are less sensitive to class imbalance, these are only ways to mitigate the issue of overtraining on the majority class (and vice versa). A radiologist will have the ability to draw from their broader clinical experience, consult with other specialists and adapt to new/unexpected findings, compared to a deep learning model which can only ultimately make conclusions on data they are trained with.

4. IMPLEMENTATION: CURRENT CHALLENGES OF DEEP LEARNING DEPLOYMENT

There is much to consider before successfully integrating deep learning models in practice. Integration with existing clinical workflows without causing disruption is a challenge, as radiology departments often use establish protocols and systems. New AI solutions must be compatible with existing imaging equipment and software.

It is difficult to implement AI in radiology without these disruptions, however these are only short term and minimising the implementation time is a priority. Flexible software interfaces should be created which is compatible with common radiological software and hardware, guided by radiologists to ensure seamless integration with existing workflows, alongside providing relevant training and support.

Additionally, deep learning models must undergo rigorous validation and regulatory approval, which can be time-consuming and expensive. Statistical results can be misleading, and it is important to not rush to deploy any seemingly 'strong' model across healthcare institutions. In the EU, medical devices must confirm to GDPR and the required CE regulations, with the UK requiring devices to be registered with the MHRA and undergo a UKCA assessment. CE marking can take from a few months to a few years, depending on the complexity and intended coverage of AI software, with similar timeframes for MHRA and UKCA.

Early involvement of regulatory bodies in the development process, conducting extensive validation studies and clinical trials to demonstrate the effectiveness and safety of deep learning applications in radiology is essential. Collaboration with academic institutions and transparency in the algorithm's decision making process is also crucial. There should be no suggestion to avoid or remove the initial need for regulation, as these implementations should be treated as irreversible in the short and long term.

Deep learning algorithms require large amounts of high-quality annotated data to be trained effectively. In radiology, obtaining such datasets are challenging due to patient privacy concerns and general poorly documented patient data which is common even in nationalised healthcare systems such as the NHS in the UK.

Larger, shared databases needs to be improved and integrated within a country's healthcare system, through cloud technologies. With appropriate training on new database systems, this will allow for the standardisation of medical data, which have a global impact where federated learning [8] can be employed, in which algorithms are trained across multiple decentralised servers to tackle data silos without sharing PII data.

5. FAIRNESS: BIAS AND VARIABILITY WITHIN ML SOLUTIONS

Deep learning algorithm unfairness can stem from biases in training data, such as overrepresentation of certain races, genders, or age groups. If these biases pervade the entire dataset, they may not be reflected in performance metrics, leading to poorer outcomes for underrepresented groups. Addressing this might involve creating multiple models for different demographics, tailored to the specific needs of local clinic populations. This approach demands more time and resources, emphasising the crucial need for thorough data exploration before model training to identify and adjust for any demographic imbalances.

Certain conditions are more prevalent in specific demographics, like coronary artery disease in South Asians or prostate cancer in older men. Yet, it's crucial for models to prioritise medical features over patient characteristics. Conditions like broken bones or appendicitis span demographics, and diseases like pneumonia, though common in the elderly, can affect all ages. Radiologists must be aware of such influences to interpret images accurately, as should the machine learning algorithm. Transparency and explainability in machine learning decision-making is vital, allowing radiologists to understand and verify predictions, ensuring medical features are considered alongside demographics.

6. ETHICS: MORAL IMPLICATIONS OF AI IN RADIOLOGY

It is important to consider the ethical impact of implementing AI in radiology. With deep learning models training with huge volumes of data, patient privacy must be prioritised via anonymisation of data, secure data storage and strict adherence to data protection regulations such as GDPR or HIPAA.

Increasing reliance on AI may lead to the depersonalisation of healthcare, where it is considered important to maintain a human element in healthcare, especially in fields such as radiology. For Hinton to suggest a complete replacement of radiology by deep learning is perhaps extreme, and a balanced approach where AI aids a radiologist's decision is preferred.

Arguably most importantly, the 'black box' [9] nature of many AI systems needs to be replaced with clear legal and ethical frameworks which define the responsibilities of all parties involved. For example, a model predicting a false negative could provide ambiguity on whether liability should fall under the ML engineer, the patient's assigned healthcare professional or even the model itself - all of which prove ethically controversial or impractical. At least with transparency and explanability of results, with healthcare professionals overseeing model predictions, the liability can be more clearly assigned and spread.

7. CONCLUSION

I maintain that Hinton's suggestion for radiologists to stop being trained altogether as extreme and appears to miss the deeper layered implications of deep learning within radiology. With a significant attribution of the field towards interventional radiology, it is clear that this will require advancements in robotics and not just deep learning which will not meet required standards in the near future.

For diagnostic radiology, the short term difficulties of AI implementation and standardisation are not to be overlooked, however the improved accuracy and inevitable continuation of a shortage of healthcare professionals are long term considerations which must be addressed. With appropriate regulation and audits, deep learning tools which are designed to assist and not replace radiologists, will prove crucial in the advancement of radiology in healthcare AI.

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