Artificial Intelligence in Medical Imaging: A Double-Edged Sword?

Abstract

In an age centred on information technology, medical imaging was one of the first few fields impacted by the implementation of Artificial Intelligence (AI) partly because of the data-driven nature of AI. Radiology happens to be a field that already has a lot of digital data to train models through deep learning *(Erickson, 2022)*; according to an IBM estimation in 2016, 90% of all Medical Big Data is imaging data *(Landi, 2016)*. I have interviewed three researchers with backgrounds in nuclear medicine, medical anthropology, and computational neuroscience in order to explore the beneficial impacts of implementing AI in medical imaging such as CT, MRI and PET, while also considering the current possible drawbacks of its implementation such as data bias and insufficient data diversity.

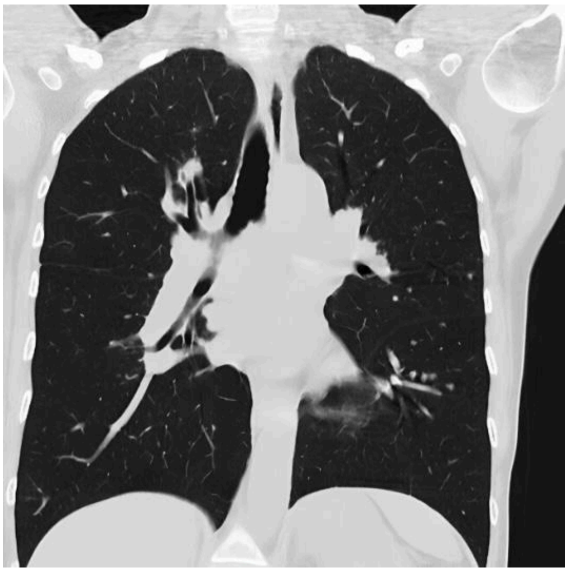
Introduction

Firstly, I would like to briefly introduce artificial intelligence (AI), medical imaging, and relevant terms that will be used to discuss later on in the paper.

The emergence of AI started in 1950 when Alan Turing proposed a test of machine intelligence called The Imitation Game in his paper "Computer Machinery and Intelligence", where the term AI was first coined. AI is a broad branch of computer science that trains machines to mimic human behaviour in order to aid humans improve performance in the field of science and technology (*Ghosh and Arunachalam, 2021*). Machine learning (ML) is a branch of AI that utilises data and algorithms to train models for complex tasks, and deep learning (DL) is a subset of ML that uses deep neural networks (multiple layers of neural networks) to imitate the complex decision-making abilities of the human brain. Neural networks are modelled on the human brain with thousands or millions of interconnected nodes, similar to how neurons work *(Brown, 2021)*.

Medical imaging, also known as radiology, is a non-invasive technology that uses sound, light, electromagnetic wave, etc., to generate visual images of internal tissues of the human body (*Jun Li et al., 2023*). In this paper, I will only mention three of the many widely used medical imaging modalities: computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET).

From my interview with an NHS Principal Nuclear Medicine Physicist, I learnt about MRI and CT scans. MRI takes advantage of the hydrogen molecules in the body, which are associated to have a spin, and when placed in a magnetic field, they point in one direction. When acquiring MRI data, the radio frequency (RF) field is switched to cause a change in polarity, giving a signal that goes through complicated computational algorithms to generate the clinical image. CT imaging, however, uses an external ionising radiation, and it fires x-ray radiation through the body. Different tissues attenuate CT through different rates, and bone attenuates much more x-ray than fleshy tissue or fatty tissue. Because the amount of radiation that you get in the detector is proportional to the density of the tissue that it has passed through, this allows it to give different images (*Chelsey Turner, August 2024, Personal Communication*). Down below is a comparison of the two scans side by side: figure 1 is an example CT scan, and figure 2 is an MRI scan (*Raksha, 2023*).



[Figure 1]

[Figure 2]

A positron emission tomography (PET) scan, on the other hand, uses a radioactive tracer through an IV drip, which shows how organs are functioning in real time. Detailed three-dimensional images of the inside of the body are produced by using two gamma ray photons that travel in opposite directions, which are then simultaneously detected by two detectors. This helps detect disease and abnormal areas (*Kapoor and Kasi, 2022*). By combining PET scans with other imaging tests, more detailed images are produced for diagnosis. For example, PET-CT scan combines a PET scan with a CT scan, while a PET-MRI scan combines PET scan with an MRI scan.

Streamlining and Increasing Accuracy – Benefits of AI in Medical Medicine

One of the many advantages of AI's application is that utilising it streamlines the processes done in medical imaging, which, NHS Principal Nuclear Medicine Physicist Chelsey Turner (*2024*) says, "For example, it allows doctors to see more patients than previously allowed, and [AI] also helps stratify for which patients to see and schedule [medical appointments]." According to Dr. Bradley Erickson (*2022*), director of Mayo Clinic's AI Lab, the implementation of ML is used to complete some of the more time-consuming work in medical imaging. Furthermore, the diagnostic capabilities of AI are what attracts a lot of the appeal. Supporting Erickson's (*2022*) statement is a study comparing four radiologists to a pneumonia-detecting model CheXNet, in which both groups examined four hundred x-ray scans. In Figure 3, the difference in performance is statistically significant with CheXNet completing the tasks better than the vast majority of the radiologists and the total radiologist average (*Rajpurkar, Irvin, and Zhu et al., 2017*). The most interesting fact, however, is that the experts took about three to four hours, whereas it took the model only one minute despite the model having higher accuracy.

	F1 Score (95% CI)
Radiologist 1	0.383 (0.309, 0.453)
Radiologist 2	0.356 (0.282, 0.428)
Radiologist 3	0.365 (0.291, 0.435)
Radiologist 4	0.442 (0.390, 0.492)
Radiologist Avg.	0.387 (0.330, 0.442)
CheXNet	0.435 (0.387, 0.481)

[Figure 3]

In the medical field, particularly in medical imaging, accuracy is one of the most crucial factors, if not the most crucial, in delicate situations which can be the deciding factor whether a patient receives treatment or not, where in cases of misdiagnosis can possibly be lethal. Research of postmortem examinations spanning several decades has consistently shown that diagnostic errors contribute to around 10% of patient deaths (*Shojonia et al., 2001*). Additionally, approximately 20 million radiology reports contain clinically significant errors (*Brady, 2017*). Medical professionals are confident that integrating AI in medical imaging will redefine the field and drastically mitigate diagnostic errors (*Najjar, 2023*).

The Possible Global Impact of Accessible Medical Imaging

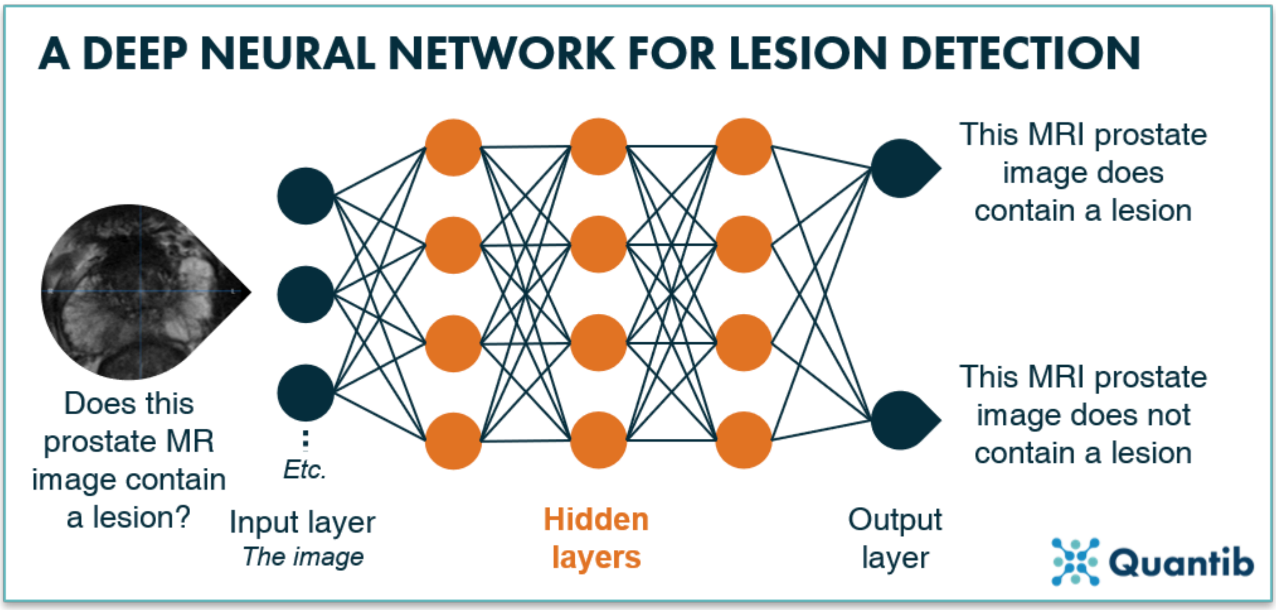
Medical imaging plays a key role in accurate and timely diagnosis, which informs and guides treatment decisions, and then contributes to improving treatment outcomes (*"Improving access to medical imaging for more patients", 2022*). The gap of medical imaging access between developed and developing countries is massive: around two-thirds of the world's population (approximately 5.2 billion) has no access to diagnostic imaging (*Maboreke et al., 2019*). Moreover, a recent study emphasised the disparity between low- and middle-income countries (LMICs) and high-income countries (HICs); LMICs only have one CT scanner per million inhabitants and HICs, on the other hand, have forty scanners per million inhabitants. Furthermore, the gap is even wider for MRI (*Frija et al., 2021*). As a result, people die of tuberculosis (TB) and lung cancer without a basic chest radiologist according to Dr. Matt Lungren (*2018*) of Stanford University. According to the World Health Organisation (WHO), TB is the second leading infectious killer with 1.3 million fatalities in 2022 which is predominant in LMICs (*World Health Organisation, 2023*).

Medical Anthropologist and Public Health Researcher Ana Paula Rubio further emphasises that the deployment of AI in medical imaging will increase the accessibility of healthcare to remote areas. AI has the potential to bridge the wide gap between LMICs and HICs. According to her, AI will likely act like a "waterfall", meaning that it eventually spreads and falls to other countries as it is deployed with the potential to improve healthcare in the long term (*Ana Paula Rubio, August 2024, Personal Communication*).

Previous initiatives like XRay4All by Stanford's Center for Artificial Intelligence in Medicine & Imagine (AIMI), which attempted to democratise radiology, would likely pave the way of accessibility by drastically eliminating some of the financial costs (*Frija et al., 2021*). All in all, the implementation of AI in LMICs will likely make medical imaging more accessible with the long-term benefits such as: improving diagnosis, reducing costs, enhancing patient outcomes and strengthening health systems. The greatest possible impact of AI in medical imaging, according to Dr. Matt Lungren (*2018*), is clinician-centred imaging tools alongside its global applications.

Data Bias and Data Diversity in AI Medical Imaging Models

The advancements in technology allow us to utilise powerful neural networks and GPUs, which run most of our lives like shopping and banking. Not only that, they are also excellent at classifying images. In my discussion with Computational Neuroscientist Robyn Greene, they mention that "AI can observe patterns not visible to the human eye." This is why AI is used in medical imaging. In order to achieve models that are accurate and reliable, the models must be trained using deep learning (DL) by using reliable medical imaging data. However, as seen in Figure 4, deep neural networks have hidden layers that turn it into a "black box" because the processes in those layers are unknown and abstracted from the user.

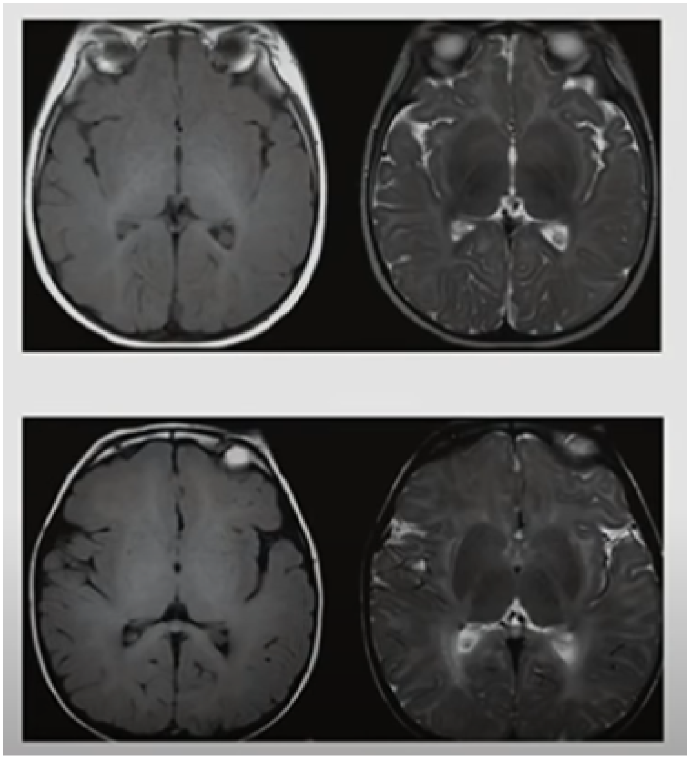


[Figure 4]

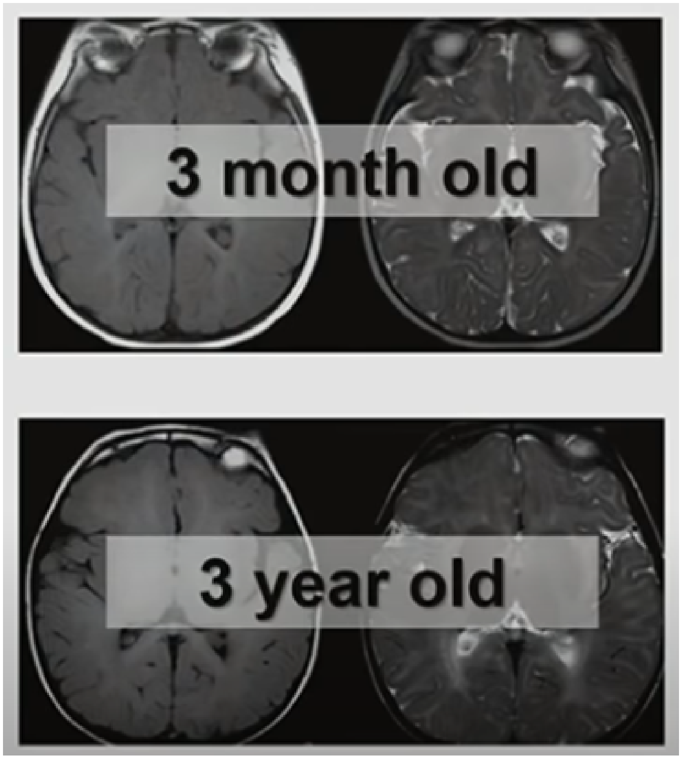
Robyn succinctly describes this as a well-established problem of "you get out what you put in", introducing the problem of data bias. Machine learning algorithms do not have the concept of morality, therefore, if we keep giving it horrible misdiagnoses, it will keep throwing back horrible misdiagnoses at us. This also means that if we trust AI models in medical imaging blindly, we will end up diagnosing people with something that they do not have. This then disproportionately affects the demographics where the data is particularly skewed. (*Robyn Greene, August 2024, Personal Communication*). An example of this is that classifiers – algorithms that automatically categorise data – trained on gender-imbalanced sets were less accurate when applied to images of the underrepresented gender (*Larrazabal et al., 2020*). Data bias is also not an issue only present in AI Medical Imaging, but it is also present in the whole field of medicine (*Ana Paula Rubio, August 2024, Personal Communication).*

Ana Rubio emphasises, however, that the overrepresented gender is not the pitfall of AI, but rather it is just the outcome resulting from the inputted data. This simply means that more and diverse data means better outcomes. Ana believes that “AI sheds light on important issues, like the lack of the diversity of data, which [opened] the discussion for data diversity and acknowledging such issues.” This gives the spotlight to the question: “Why are we raising these questions in the first place?” In Scotland, for example, macular degeneration is prominent, but there is not enough data for people of afro-caribbean backgrounds. However, data diversity isn’t the core issue; rather, it’s about aligning the dataset with its intended purpose. For example the lower prevalence of AMD in Black populations suggests that datasets should be purpose-built to address the specific health needs and characteristics of the target group, rather than simply aiming for broad diversity (*Ana Paula Rubio, August 2024, Personal Communication)*.

Challenges in Medical Imaging: Context and Artefacts
When using AI in medical imaging to scan and diagnose patients, having the correct context is critical. If medical imaging models do not have the right contexts, the model will possibly describe wrong labels, which can lead to disastrous consequences. For example, Figures 5 and 6 show identical medical scans, without context. However, the 3 month old is completely normal, whereas the 3 year old has a severe neurological disease with a delay in myelination. This emphasises that context is very crucial when using models to diagnose patients (*Lungren, 2018*).



[Figure 5]



[Figure 6]

An artefact is when an abnormality that does not reflect the anatomy or pathology of the patient is scanned. These are caused by the patient's movement, equipment malfunction, or the image reconstruction algorithm. Artefacts can lead to misdiagnosis, overdiagnosis or delayed medical intervention (*Erasmus et al., 2004*). To prevent and minimise the risk of artefacts, use improved data quality as well as diverse datasets, calibrate equipment regularly, and implement better AI models. Figure 7 shows an example of an artefact caused by unremoved clothing and Figure 8 shows a stitching line.

[Figure 7]

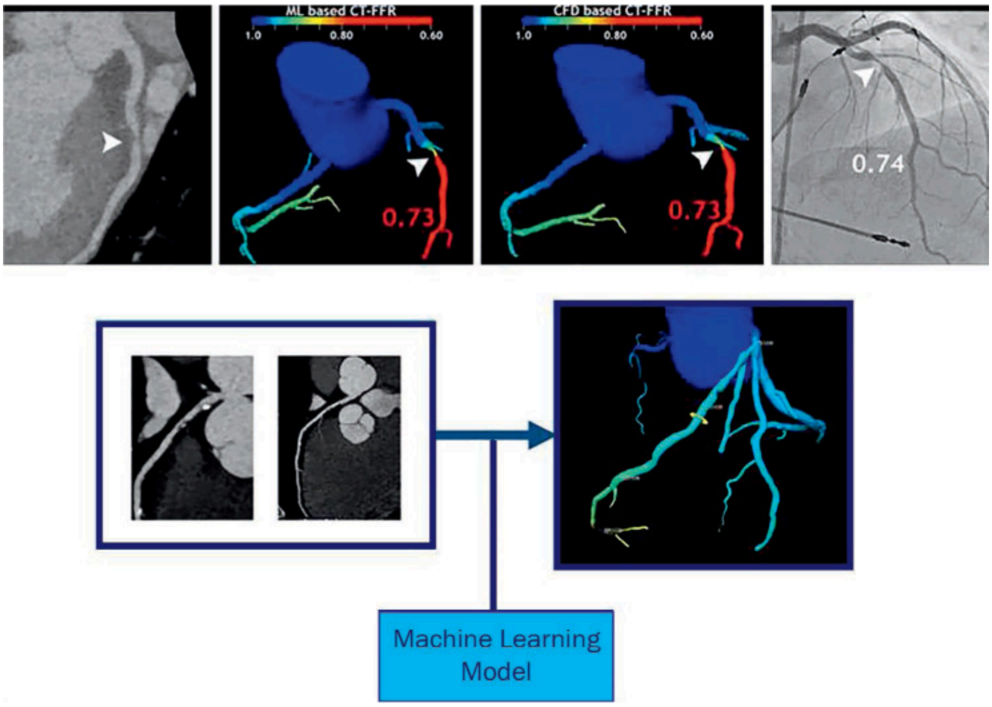
[Figure 8]

Predictive Capabilities of AI in Medical Imaging

AI is not only used to identify current disease and abnormalities, but one of its benefits is its ability to predict diseases such as a heart attack for patients it identifies at risk beforehand. In a machine learning context, the model will be trained on recent patient diagnoses for heart attack by using a supervised method. By using a supervised method, we are essentially training the algorithm to provide two possible outputs: this person is at risk of a heart attack and this person is not at risk of a heart attack. The model tries to cluster symptoms by using the symptoms and illnesses the patient already has, which is then used to create a classifier. A classifier, as mentioned briefly in the previous sections, is an algorithm that sorts the data based on certain characteristics, which in this case is someone with or without the risk of a heart attack (*Robyn Greene, August 2024, Personal Communication*).

Recent advancements by a research team at the University of Oxford has now enabled an AI model that accurately predicts the risk of heart attack, heart failure or cardiac death simply from routine medical scans ten years in advance. Dr. Kenneth Chan, a research fellow at the university, mentions the capabilities AI in medical imaging can do that humans alone cannot: "The AI technology can detect the level of inflammation of the heart arteries, by detecting changes in the fat tissue around arteries that are not visible to the human eye. In this way we can identify patients with high inflammation and high risk" (*Chan et al., 2024*)

Figure 9 illustrates an AI model that can analyse CT scans in assessing coronary heart disease by calculating how severe the narrowing of the arteries is by measuring blood flow, demonstrating AI's potential to predict future cardiac events by detecting subtle signs.



[Figure 9]

Conclusion

Despite the current issues at hand due to the abstracted nature of deep learning in medical imaging and not fully understanding the in-between of the input and the output, the application of AI technology today can be seen tackling pressing issues such as diagnostic errors with its capabilities to improve diagnostic accuracy and aid medical experts by streamlining their processes. Data bias and diversity, as I explored in this paper, are also current issues not because of the outputs given by current models, but because datasets should be purpose-built for specific health needs, rather than blindly aiming for broadly generalising the models.When utilising AI in medical imaging for patient diagnosis, ensuring the correct clinical context is crucial; without it, models may produce incorrect labels and lead to serious misdiagnoses, as demonstrated by the differences between Figures 5 and 6, where identical scans could result in contrasting conclusions due to a lack of contextual information. Without careful consideration of context and artefact management, AI models risk producing misleading outputs that could lead to serious consequences for patient care.

Looking ahead, the application of AI in medical imaging has the potential to bridge healthcare gaps in LMICs and HICs, and revolutionise healthcare. As the technology advances, AI's role is likely to evolve and expand for early detection, personalised treatment and overall patient outcomes.

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