Bridging the Gap between Medical Imaging and Artificial Intelligence

A Research Paper submitted to the Department of Engineering and Society

Presented to the Faculty of the School of Engineering and Applied Science

University of Virginia • Charlottesville, Virginia

In Partial Fulfillment of the Requirements for the Degree

Bachelor of Science, School of Engineering

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Spring 2023

On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

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Introduction

Applications of artificial intelligence (AI) in medical imaging have the potential to provide substantial aid in areas such as disease diagnostics. It has shown impressive accuracy in automatically segmenting anatomical structures and analyzing imaging data to identify abnormalities that would otherwise be time-consuming, laborious, and subjective when done manually by clinicians. However, AI-based imaging systems lack transparency in how and why a medical analysis is made. This discourages the use of AI models and diminishes trust in their reliability. The goal of this paper is to describe the gap between the research of machine learning-based techniques in medical imaging and its implementation in healthcare to discuss ways that AI models can be constructed in an explainable manner. This will require robust oversight and guidance that will ensure acceptance by its users (Mudgal & Das, 2019).

To answer our STS question, “How do we bridge the gap between the research of AI-based techniques in medical imaging and its implementation in healthcare?”, Actor-Network Theory (ANT) will be used as an approach to understanding the interactions between clinicians and AI-based medical imaging algorithms, the black box. A black box has internal processes that are unknown and invisible, and this makes AI unclear. The STS paper will assist in modifying AI systems to be understandable from a clinician’s point of view. Documentary research methods will also be used, complimentary to ANT, to provide perspectives directly from medical professionals, especially those who specialize in diagnosing diseases using imaging. This involves collecting sources from articles, analyzing documentary evidence, and explaining the significance.

Background

Medical imaging is used to view parts of the body to diagnose, monitor and treat conditions. The most common modalities for imaging tests are PET, fluoroscopy, ultrasound, MRI, CT, and X-ray (*Imaging*, n.d.). They are often used before and after surgeries to get data about a patient's condition and track disease progression. While the images themselves offer lots of insight for doctors, it is the quantified functional parameters that assist in providing physiological information and are a crucial component for clinical evaluations.

For example, the ejection fraction, which refers to the percentage of blood that is pumped out of a filled ventricle with each heartbeat, is commonly quantified from MRI and ultrasound (*Ejection Fraction*, n.d.). However, such measurements rely on accurate segmentations of the left ventricle which has traditionally relied on hand-drawn segmentations which are prone to variability. The process is time-consuming for clinicians and there are underlying biases that could lead to clinical consequences such as an inaccurate diagnosis. In the biomedical engineering field, research is being conducted to create deep learning-based quantification of clinical parameters such as the ejection fraction.

Almost one in four patients experience false positives on image readings (*Consider the Promises and Challenges of Medical Image Analyses Using Machine Learning*, 2020). This could lead to unnecessary procedures and follow-up scans that add stress and cost for patients. The application of AI, the term used to describe the use of computers and technology to stimulate intelligent behavior and critical thinking comparable to a human being, in medical imaging analysis has great potential in the ability to reduce errors by accurately characterizing pathologies and recognizing complex patterns in an automated fashion (Amisha et al., 2019). However, AI will not replace doctors; the clinical workflow would involve both humans and AI working together with human readers needed to verify accuracy. AI systems aim to assist clinicians in making the clinical diagnosis process more standardized and reduce inter- and intra-subject variability by using accurate, efficient and reproducible AI-based radiology assessments (Hosny et al., 2018).

While research being done with AI is causing a paradigm shift in the way medical images are analyzed and quantified, their implementation in the clinic has been questioned because of AI's uninterpretable black box nature. The interactions between users and tools must be analyzed to see how they can be seamlessly integrated into the workflow. This will allow for a better understanding of how the design of AI-based analysis in healthcare can be user-centered and more interpretable.

Actor-Network Theory

ANT is a science, technology, and society (STS) framework, proposed in the early 1980s, that attempts to "open the black box" of science and technology (Cressman, 2009). It seeks to understand how human and nonhuman actors form alliances in a network of interactive relationships (Crawford, 2020), rather than analyzing actors as isolated individuals. In any network, there are actors (such as people, tools, or technology) that play an active role in the overall system. They have connections to each other and influence one another; the nonhuman actors have an impact on human actors and vice-versa.

According to ANT, actors do not hold power; the analysis focuses on how actors associate with other actors. In this regard, the networks of interactions that actors form are a "translation" process, a key tenet of ANT. Actors and networks are not fixed; they are always evolving as they interact with each other. The translation process involves the creation of modified relationships between actors as they modify their goals in response to new interests.

As actors move between networks, new relationships are formed. This can involve disengaging actors from other networks. Overall, the ANT perspective works to understand the interactions between actors and their contributions to a network. This requires understanding how networks are created and maintained, and how actors can be transformed through their interactions as their interests change.

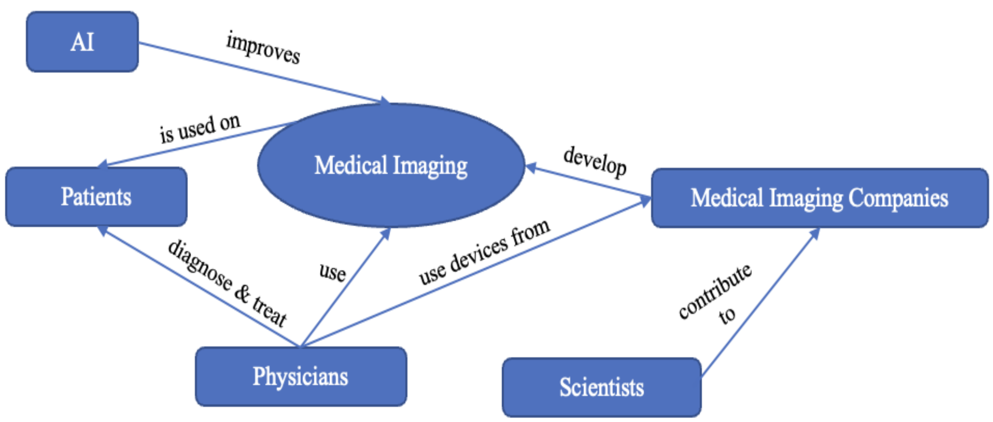

Figure 1. Actor-network map of an inadequate network for implementation of AI-based medical imaging in healthcare.

The ANT framework will be used in this STS topic because it highlights how interactions among actors change in dynamic networks. In this case, our actors are physicians, AI, patients, scientists, and medical imaging companies (Figure 1). The field of medical imaging analysis is taking an increasingly important role in clinical decision-making and biomedical engineering researchers are working to make the process more time-efficient and accurate using AI (Oksuz et al., 2020). Applying ANT, for AI-based techniques to be implemented into clinics, changes must be made in the design of AI models, so it suits the “interests” of the clinician. In Figure 1, an actor-network map is displayed when an unexplainable AI system is implemented; there is a lack of transparency which makes it difficult to decipher an AI’s result.

Black Box - AI

The black box must be demystified to convince radiologists to use AI in their analysis. By doing this, radiologists would accept a modified medical imaging network that uses AI. The understandability of this network is important as using AI to analyze images was not likely done in their clinical training. The traditional time-consuming medical imaging network will eventually be replaced by one where AI and physicians work together efficiently. According to ANT, there is no unbalance in power between the two actors. The physician and AI work together to produce accurate medical imaging diagnoses. This is well stated by physician-scientist Dr. Antonio Di leva, “Machines will not replace physicians, but physicians using AI will soon replace those not using it” (Ieva, 2019).

Firstly, to design more interpretable AI, it must be understood why and how AI is associated as a black box. The concept of black box in ANT highlights the uncertainties in understanding an actor and is used to describe a technical object that operates as it should, but its complex sociotechnical relationships are rendered invisible. An actor has a black box nature when its internal processes are unknown, and it is not fully understood how it works. For example, mistakes made by AI would cause more confusion than mistakes made by humans. In other words, physicians using AI-based tools would not be able to tell when and why a mistake has occurred or how to fix it because AI itself is unclear and a black box (Liang, 2022). This causes physicians to hesitate in trusting the results of AI because it appears as a magical uninterpretable output.

Physicians

The interest of the physician is to be part of a medical imaging network where the actor tools are understandable. From the research and AI point of view, the development of tools is generally focused on the technicality of developing algorithms and convolutional neural networks that yield accurate results. According to ANT, to align the interests of the two actors, AI-based medical imaging analysis should have user-centered integration designs. This suggests that the focus in the development process of AI models is not only the output, such as a quantified clinical parameter, but also other information that would allow for the comprehension of AI's findings. In this network, physicians would be more inclined to use the AI tool because they can decide whether to trust the finding and it allows physicians to collaborate with AI.

Providing additional documentary research, British cardiologist Dr. Paul Wood said "There is already evidence that we are in danger of losing our clinical heritage and of pinning too much faith in figures thrown up by machines. Medicine must suffer if this tendency is not checked" (Vartabedian, 2011). According to his words, Dr. Paul would not have willingly joined a network that uses solely AI-based medical imaging analysis. There needs to be an interaction between the physician and AI as AI is not replacing physicians; it is assisting them as a partnership. Yet oftentimes, researchers in the field will validate their work by measuring AI against physicians instead of measuring how AI might augment the work of physicians (Langlotz, 2019).

Patients

Next, the views of patients on the clinical integration of AI in medical imaging must also be discussed. Some patients may be concerned that technology could be less accurate than a physician's interpretation and others may be accepting of AI if they believe it to be more accurate and improve time-efficiency. Generally, their interests are to receive a correct diagnosis when going to the doctor's office, with or without AI as long as there are no unintended consequences such as higher health care costs, privacy breaches and misdiagnosis (*How Do Patients Feel About Using AI in Health Care?*, n.d.).

A research team from Yale Cancer Center surveyed 926 patients regarding their perspectives on AI in healthcare. Most respondents believed that AI would make healthcare much better or somewhat better, with overall positive views about AI. When asked a question regarding the use of AI reading medical images, specifically if they were comfortable with AI reading chest radiographs, 42.7% of respondents were somewhat comfortable and 12.3% were very comfortable. However, 25.2% were somewhat comfortable and only 6.0% were very comfortable about AI making a cancer diagnosis.

Dr. Sanjay Aneja, a radiation oncologist and senior author of the research, said "Patient education, concerns, and comfort levels should be taken into consideration when planning for integration of AI" (*How Do Patients Feel About Using AI in Health Care?*, n.d.). Notably, one of the key findings from the team is that patients of racial and ethnic minority groups responded being very concerned about issues in AI when compared with white patients (*How Do Patients Feel About Using AI in Health Care?*, n.d.). It is generally not the black box nature of AI that concerns patients but rather simply whether it works which heavily relies on the training data of the machine learning model. The training data must be diverse to ensure that the AI model is robust and effective. If the data is biased by only including images of light-skinned patients, then the algorithm will not perform accurately for patients with darker skin. Not all medical data sets available are diverse and it is crucial for the models being implemented in healthcare to be representative of all patients by using data from patients of different racial and ethnic backgrounds. Doing so will reduce bias and improve accuracy of AI results.

Medical Imaging Companies

Another perspective to be considered in the network is medical imaging companies, which manufacture and distribute medical imaging devices such as MRI machines. Their developments rely on scientists, and they are leveraging AI to address healthcare challenges. When there is a need, such as managing the increasing workload of radiologists, companies seek to address it. Studies report that an average radiologist must interpret one image every 3-4 seconds in a workday (Hosny et al., 2018). These constrained conditions that require decision-making and visual analysis make errors inevitable, so many medical device companies such as Siemens Healthineers, Philips and GE Healthcare are providing AI as a new toolset for physicians to utilize.

In an interview for Forbes, Vignesh Shetty, SVP & GM Edison AI and Platform, GE Healthcare Digital shares how GE Healthcare is applying machine learning in healthcare technology (Walch, n.d.). He says that practitioners and developers are “passionately striving to solve the same problems but not necessarily talking to each other, early enough. The result is that some offerings do not address the right clinical or operational need, are not suitably integrated into existing workflow, or simply do not work” (Walch, n.d.). Shetty also has a similar “interest”, in the ANT sense, that AI will not replace physicians; it is a “new lever” to amplify physicians’ work. Hence, AI systems must have user-centered integration designs.

Medical imaging companies recognize that the main obstacle for physicians in adopting AI is its unfamiliarity. Building trust will lead to its utilization and unleash AI’s potential. One way of doing this is by building explainable AI systems which can be a key driver of adoption and enable more optimal collaboration (Gaube et al., 2021). Based on ANT, the formation of a more transparent medical imaging network by creating interactions between its actors (scientists, AI, patients, physicians, and medical imaging companies) will create more trust in AI-based medical imaging analysis.

Collaboration

In building an explainable medical imaging AI system for clinical implementation, partnerships must be made between basic and clinical scientists. Dr. Ilias Attaye, MD, a Ph. D. candidate and Fulbright Scholar said “there is a disconnect between the two disciplines” (Elsevier, n.d.) which “means you miss a lot of opportunities to understand how each field works, but also to exchange ideas” (Elsevier, n.d.). To amend this, by ANT, the network must be modified.

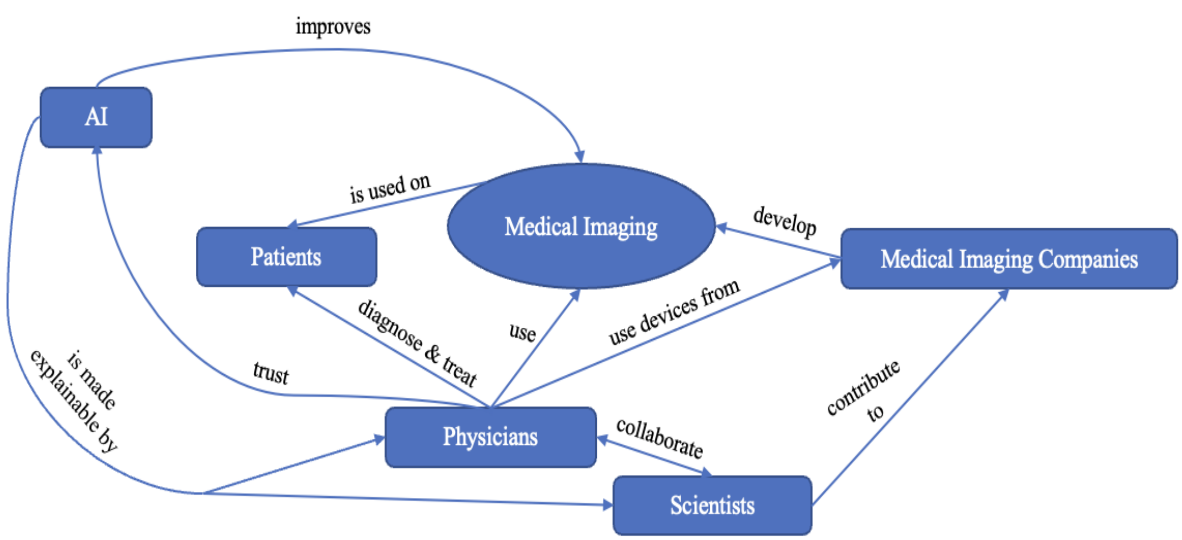

Figure 2. Actor-network map of an adequate network for implementation of AI-based medical imaging. in healthcare.

As seen in Figure 1 and Figure 2, several actors play a role in the medical imaging network. As shown, each actor has a different function and is involved in different relationships. The main difference between Figure 1 and Figure 2 is the increased interconnections between AI, physicians, and scientists. This assists in understanding how to use AI-based techniques in medical imaging and helps in the interpretation and translation of each actor’s behavior and interests. In Figure 2, physicians trust and use AI as they oversee its outcomes and validate it. This is important to make sure nothing was overlooked that the human physician expertise would have caught.

Conclusion

The STS analysis for bridging the gap between medical imaging and AI shows the need for a user-centered interpretable design for AI-based systems. To develop these so physicians are involved in the pipeline work on AI medical imaging analysis, connections must be made between the actors of the network; this will demystify the black box nature of AI as physicians gain awareness of how quantified clinical parameters come about.

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