Deep Learning-Based Motion Correction for Cardiovascular Magnetic Resonance Imaging
(Technical Paper)

Bridging the Gap between Medical Imaging and Artificial Intelligence
(STS Paper)

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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

In the United States, about 600 million medical imaging procedures are performed annually (*Medical Imaging - an Overview | ScienceDirect Topics*, n.d.). Processing of these medical images is a major diagnostic and prognostic tool. However, it is a time-consuming process, difficult to manually examine, and prone to variability. Almost one in four patients experience false positives on image readings (*Consider the Promises and Challenges of Medical Image Analyses Using Machine Learning*, 2020). Inaccurate evaluations of medical images can lead to unnecessary procedures and follow-up scans that add stress and cost for patients. The application of artificial intelligence (AI), particularly deep neural networks, to enable automatic analysis of medical imaging is playing an increasing role in biomedical research. However, these techniques are black boxes among clinician end users, where very few understand what processes lead to a given result. The final STS deliverable will be on bridging the gap between the research of machine learning-based techniques in medical imaging and its implementation in healthcare.

For the capstone project, deep learning will be utilized in cardiovascular magnetic resonance (CMR) to correct motion-induced artifacts. CMR perfusion, a noninvasive diagnostic imaging technique, is often performed during a single breath-hold to limit the movement of the heart. However, patients often have limited breath-hold capacity and involuntary motion of the diaphragm often occurs (Pontré et al., 2017), leading to motion artifacts caused by breathing. Motion correction must therefore be performed for accurate quantification of blood flow to assess cardiac function. The final technical deliverable, deep learning-based motion correction for CMR perfusion, will correct artifacts to generate good quality and reliable images for immediate clinical interpretation.

Deep Learning for Motion Correction of Cardiovascular Magnetic Resonance Imaging

Cardiovascular diseases are a leading cause of death globally, taking an estimated 17.9 million lives each year (*Cardiovascular Diseases*, n.d.). CMR imaging is the reference modality for non-invasive assessment of cardiac function by computing ventricular volumes to assist in the diagnosis of cardiovascular diseases. Analysis of such medical imaging is taking an increasingly important role in clinical decision-making, and assurance of image quality is an important step because high accuracy in downstream tasks such as segmentation depends strongly on high-quality medical images (Oksuz et al., 2020). For example, artifacts in CMR lead to poor image quality, repeated scans, and remain an obstacle to clinical use (Bush et al., 2019). Inter-frame motion artifacts make quantitative analysis for cardiac function evaluation difficult. Hence, motion correction is an important pre-processing step before robust quantification of myocardial perfusion analysis (Pontré et al., 2017). The traditional method for correcting motion-induced artifacts from cardiac and respiratory motions, Advanced Normalization Tools (ANTS), is a time-consuming optimization-based method. This capstone proposes to develop a deep learning-based framework for motion correction of CMR that will enable faster image registration to quantify the time-series data, improve the visual evaluation of CMR images, and automatically correct motion-related artifacts. The technique will be used on CMR image cases of human hearts and will evaluate its time efficiency and accuracy.

A deep learning-based respiratory motion correction framework will be developed by deploying an existing deep learning model and applying it to cardiac magnetic resonance first-pass dynamic perfusion imaging. Then the model's ability to correct motion-induced artifacts will be improved by exploring different network structures.

The aims will be completed by developing and executing code in Python to design a convolutional neural network (CNN) for motion correction for CMR perfusion; existing deep learning models to deploy include VoxelMorph (Balakrishnan et al., 2019), an unsupervised deep learning-based registration method that has been demonstrated on the task of brain MRI registration, due to its high accuracy and ease of training methodology. The network will be improved for CMR by modifying the architecture of the network. Completion of these aims will create an automated approach for motion correction of CMR using deep learning. The deep learning-based technique will reduce motion artifacts and improve image quality efficiently, taking less time than ANTS to enable immediate clinical interpretation and diagnosis of cardiovascular diseases.

Concerns for Implementation of Artificial Intelligence-Based Techniques in Healthcare

Medical imaging is a class of imaging technology to understand the human body by noninvasively creating visual representations. Its use for diagnosis remains a time-costly and uncertain process for clinicians. There is a need for automatic methods that analyze medical imaging data. In medical imaging, research, especially in biomedical engineering, is being conducted to automatize many of the analyses that radiologists must do in the detection, characterization, and monitoring of diseases. AI, the term used to describe the use of computers and technology to stimulate intelligent behavior and critical thinking comparable to a human being, has promising diagnostic accuracy with deep learning (Amisha et al., 2019). AI methods excel at automatically recognizing complex patterns in imaging data and providing quantitative, rather than qualitative, assessments of radiographic characteristics (Hosny et al., 2018). Yet there is resistance to adopting AI-based diagnostics in clinics (Liang, 2022) because of the black-box nature of the algorithms. Biomedical researchers must demystify this black box by providing avenues that give explanations to doctors and involve them in the system pipeline.

To analyze the gap between the usage of AI-based techniques and its implementation in healthcare, the framework of Actor Network Theory (ANT) will be utilized. ANT is an approach to understanding humans and their interactions with inanimate objects (Cresswell et al., 2010). Earlier in this discussion, the use of AI in medical imaging analysis was described to be a black box by clinicians. In Darryl Cressman's *A Brief Overview of Actor-Network Theory: Punctualization, Heterogeneous Engineering & Translation*, the term black box is used to describe a technical object that operates as it should, but its complex sociotechnical relationships are rendered invisible. For this STS topic, AI is a black box as it is a working method however it is not trusted by clinicians. AI systems will be able to provide clinical benefits if the physicians using them are able to balance trust and skepticism (Gaube et al., 2021). Key stakeholders, physical artifacts, and non-physical artifacts for bridging the gap between clinical implementation of AI and medical imaging include the following: medical imaging modalities, medical imaging manufacturers, medical imaging services, AI algorithms/models, patients, and medical professionals. While ANT distinguishes itself from other sociotechnical approaches by considering both human and non-human elements equally as actors within a network, it does not consider "intangible" elements such as values and norms. ANT instead focuses on empirical observation that does not fully encompass a given topic (Cressman, 2009). Regarding the use of AI in medical imaging, ANT would ignore topics such as an experienced radiologist's preference to refrain from learning new AI-based analysis after already being trained.

Researching and analyzing AI in medical imaging through an STS perspective will help in understanding what modifications may be made in AI systems to make them more transparent and understandable from a clinician's viewpoint. The majority of AI being developed in medical imaging aims to assist radiologists in segmentation and image detection to quantify anatomical parts and help in the early detection of disease. In the future, radiology is deemed to be most benefited from workflow algorithms aiding real-time image quality assessment, creation of study protocols for follow-ups, and increasing image quality from noisy low-quality images. To have such developments be implemented in the clinic, it requires robust oversight and guidance that will ensure acceptance by its users (Mudgal & Das, 2019).

Research Question and Methods

The STS question is: How do we bridge the gap between the research of AI-based techniques in medical imaging and its implementation in healthcare? To answer the research question, documentary research methods will be used with a variety of sources ranging from scholarly articles to peer-reviewed journals. These include Ahmed Hosny's *Artificial intelligence in Radiology* from Harvard Medical School in the Department of Radiation Oncology. By utilizing document research methods, an understanding of AI methods in image-based tasks will be established and the challenges facing clinical implementation will be discussed by providing perspectives from medical professionals. These perspectives will assist in identifying how AI models for medical imaging analysis can be more transparent and trusted by clinicians. The key words to research include "artificial intelligence in radiology," "black box AI," and "explainable medical imaging models." These keywords are selected to collect research because they encompass the different components of the STS topic such as viewing AI as a black box, AI techniques in radiology, and how AI models can be made explainable.

Conclusion

This prospectus covers an investigation of how AI models in medical imaging are viewed by clinician users as well as the technical topic of using deep learning to correct motion-based artifacts in CMR. A CNN will be deployed with inputs of a fixed and moving image to calculate the deformation field and output a motion corrected image. It is expected that the process of acquiring these results from the developed model will be faster than ANTS. These results will assist radiologists in their clinical duties by providing good quality images that are not disrupted by blurring artifacts which would otherwise affect a physician's evaluation of the image.

On a similar note of usage of AI in medical imaging, this paper explores how clinicians view using AI in medical imaging analysis, specifically its black box nature. Biomedical engineers are conducting research in medical imaging, an interdisciplinary field, by using AI in order to improve the clinical utility of imaging modalities such as MRI. However, the vast majority of doctors, not having an engineering background, can be skeptical of the analysis especially with the black box nature of AI. Analysis of these interactions will be done using the ANT framework to identify ways that AI models can be constructed in an explainable manner.

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