Using Deep Learning to Segment Coronary Artery CTAs, Hypertrophic Cardiomyopathy MRIs, and Hydrocephalus Ventricle CT Scans
(Technical Paper)

Optimizing the Integration of Computational Tools in Routine Clinical Cardiology
(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.

Introduction

With every minute a cardiologist takes to diagnose a critical cardiac condition, a patient's window for effective treatment is drastically reduced. Modern day physicians are put under a great deal of pressure to accurately diagnose complex diseases while provided with miniscule information and an unfavorable amount of time. Computational tools, such as predictive modeling and artificial intelligence, are valuable tools for physicians to effectively diagnose and treat patients (Liu et al., 2020; Niederer et al., 2019). In healthcare, medical images have become ubiquitous for preventative disease screening, disease diagnosis, and treatment selection for patients (Bercovich & Javitt, 2018). As a result, medical images must be quantitatively analyzed using manual image segmentation, a process to differentiate anatomical regions; however, manual segmentation is laborious and time consuming for physicians and often leads to inter-observer biases (Merjulah & Chandra, 2019).

The technical portion of this proposal leverages deep learning convolutional neural networks (CNNs) to quickly and efficiently segment coronary arteries from Computed Tomography Angiographies (CTAs), myocardial scarring from Magnetic Resonance Images (MRIs) of hypertrophic cardiomyopathy patients, and neural ventricles of hydrocephalus patients from Computed Tomography (CT) scans.

Although complex computational tools like deep learning can be used to advance patient diagnoses, there are often several barriers to integrate these tools into hospitals such as cost of tools, physician acceptance, and difficulty of using the computational tools (Coye & Kell, 2006; Lee et al., 2014). Thus, the sociotechnical portion of this proposal will analyze what factors are needed to successfully integrate computational tools in routine clinical cardiology and how engineers can modify their design approach to ensure cardiologists use the computational tools.

Technical Topic – Deep Learning Medical Image Segmentation Algorithm Development

Considering medical professionals must undertake a multitude of tasks, maintaining high efficiency when completing any given task is of utmost priority. Quantitative evaluation of medical images from CT or MRI improve the accuracy and reliability of diagnosis by extracting imaging biomarkers, which are measurable indicators of a disease state, to provide insights such as probability for disease progression, intensity of disease presence, and other numerical features about the physiology and anatomy from the image (Kim et al., 2015). Unfortunately, most current clinical processes rely on qualitative interpretation of the images by radiologists, and current quantitative methods are very laborious. Identified below are three disease states of interest that require improved quantitative medical image analysis.

Coronary artery disease is classified by the narrowing of the arteries via a buildup of plaque, limiting the blood flow to the heart, and often leads to a heart attack (Mayo Clinic, 2020). Coronary artery disease is the most common type of heart disease, killing over 350,000 people in 2017, and affecting 18.2 million adults above the age of 20 in the United States (CDC, 2020). Current identification of coronary artery disease mainly consists of manually examining CTAs for the presence of calcification and plaque residues (Arnett et al., 2019). The manual approach of identification suffers from being too time-consuming; however, through automated CTA segmentation, the narrowing and calcification of the coronary arteries can be quantified in a timely manner.

Hypertrophic cardiomyopathy (HCM), a disease with a prevalence of 1 in 200, is characterized by unexplained enlargement of the heart's left ventricle (LV), misalignment of cardiac fibers, and cardiac scarring, all of which can lead to cardiac dysfunction (Kramer et al., 2015; Olivotto et al., 2011; Semsarian et al., 2015). Most HCM cases are genetically inherited and can gradually progress towards heart failure and cardiac arrest (Watkins et al., 2011). Current identification methods for HCM include genetic testing and manual segmentation of cardiac magnetic resonance (CMR) images for unexplained LV wall thickening and scarring (Wigle et al., 1985). Automating CMR image segmentation allows for more efficient patient diagnosis and condition monitoring, ultimately improving personalized patient care.

Hydrocephalus affects 1 million people in the United States; it is very common in children as 1.1 out of every 1000 infants will develop hydrocephalus (Tully & Dobyns, 2014). It is characterized by the buildup of fluid in the ventricles deep in the brain due to increased pressure which can damage brain tissues and cause severe disabilities (Hamilton et al., 2016). Currently, manual image segmentation is used to identify areas of brain ventricles. Automating the segmentation of the images allows physicians more efficiently estimate ventricular abnormality and distinguish between chronic and acute hydrocephalus.

In each of the three disease states discussed above, manual segmentation of the medical images is arduous and time consuming for physicians. The manual segmentation process also leads to inter-observer biases and causes poor diagnoses (Merjulah & Chandra, 2019). Innovation through the creation of an improved automated process is required for improved segmentation efficiency. There have been several recent advances in using artificial intelligence to automatically segment medical images to take over the manual segmentation process. Deep learning CNNs allow for image classification where images are fed through a series of convolutions to extract image features for classification. For segmentation, different regions of the images are classified.

The goal of the project is to develop and validate deep learning segmentation algorithms for regions of interest in CT and MRI scans as well as implementing these algorithms into a medical software package. Medical images for each of the aforementioned disease states will be segmented for their regions of interest using a CNN. For coronary artery segmentation, innovative multi-channel inputs about the prior shape of blood vessels will be fed into the CNN. For HCM scar and LV wall segmentation, the goal will be to evaluate the patient population generalizability of an improved segmentation algorithm. For hydrocephalic brain ventricle segmentation, most automatic segmentation algorithms take MRI input; however, the project will use CT scans as inputs for increased spatial resolution. Automated segmentation results will be compared against manual image segmentation as a metric of success.

Considering medical professionals must undertake a multitude of tasks, they must maintain high efficiency when completing any given task. Presenting deep learning algorithms to physicians in their raw form creates potential for unintended modification of the algorithms, thus creating technical issues, reducing efficiency, and compromising patient care. Therefore, complementary to developing the segmentation algorithms, we also propose creating a universal software application to house and black box the underlying automated segmentation algorithms. Creating a user interface (UI) that prioritizes simplicity, intuitive use, and extensive user control grants physicians the power to see biomarker information in as much depth as needed while avoiding common problems, such as electronic medical record click fatigue, that plague physician interactions with software (Collier, 2018). Therefore, a software application for the automated segmentation algorithms makes them more likely to be used in the clinic.

During the fall of 2020, the research team will become accustomed to the pathophysiology of the diseases of interest, deep learning algorithms, and software tools for development. During the spring of 2021, we will develop our deep learning algorithms, and after validation, the algorithms will be packaged into a user-friendly software application.

STS Topic – Integrating Computational Tools in Routine Clinical Cardiology

The days of a cardiologist diagnosing and treating patients using solely his/her intelligence and intuition are coming to end. Rather, it takes a cardiologist working closely with an array of computational tools to provide the best personalized medical solutions for patients.

Computational tools in cardiology include artificial intelligence, biophysical and mechanistic computational models of the heart, cardiac drug kinetic models, and computer assisted decision making tools, and computer assisted therapy, to name just a few (Cuocolo et al., 2019; MEHTA et al., 1994; Niederer et al., 2019; Trayanova et al., 2012). The goal of computational tools in cardiology is to combine physiological and physical principles to understand what is happening during a pathophysiological state of the heart (Niederer et al., 2019). Artificial intelligence can be used for predictive analysis and risk assessment of various disease conditions, automatic image segmentation of cardiac images, analysis of electrocardiograms, and genomics analysis (Cuocolo et al., 2019). A computer-aided decision support system can analyze vast amounts of patterns and make detailed accurate diagnoses which can aid physicians (Cahan & Cimino, 2017). Advances in medical imaging and catheter measurements have allowed engineers to build computational models of the heart which allow researchers and physicians to understand what happens to the heart during various disease states and interventions. For instance, cardiac resynchronization therapy is a treatment for patients with dyssynchronous ventricular contractions, which is a disease state that often leads to heart failure. Unfortunately, 30% of patients who get pacing therapy do not respond well to it (Thomas et al., 2019). An electromechanical computational model of the heart can be used to determine what are the precise locations for the cardiologist to pace the heart for each person. The result is a much better treatment success rate and also alleviates pressure on the cardiologist to choose the right spot to pace (Sermesant et al., 2009).

In cardiac surgery, finite element models of the heart, detailed computational models of the geometric and mechanical properties of the heart, are used to simulate different types of surgery. For instance, in mitral valve surgery, where the mitral valve of the heart is repaired, the interventions a surgeon might introduce to the mitral valve can be simulated. The results of the surgery can be predicted without ever making a single incision in the patient (Lee et al., 2014).

Although these computational tools seem great in theory and experimental trials, there are several barriers to integrate these tools successfully into clinical cardiology for routine use. In general, hospitals have a difficult time integrating new technology into their workflows. From the physician's standpoint, two of the main obstacles are physician preferences and reactive posture (Coye & Kell, 2006). The physician must prefer the new technology for it to be adopted. In cardiology, the cardiologist must know about the new technology and actively show a patient and/or community need for it. Physician preference relates to reactive posture which is that for a hospital to adopt a new technology a physician must request it, or other hospitals must request it for a planning process to start. Coye and Kell 2006 emphasize that adopting the new technology often leads to organizational distress and grid lock. There are also financial considerations for hospitals such as the pay-to-performance ratio and the input of stakeholders involved (Coye & Kell, 2006). Ultimately, a hospital is still a business.

In a case study about computational tools in cardiac surgery, Lee et al. 2014 discusses three technical challenges of integrating surgery simulation tools in the clinic: software, hardware, and implementation issues. In terms of software issues, the finite element simulations are computationally expensive and take a long time to run. For time sensitive surgeries, it is difficult to get timely results from the model. In terms of hardware issues, it is difficult to run these complex simulations on hospital desktop computers due to poor infrastructure. In terms of implementation issues, the author mentions that cost effectiveness is a key factor for hospitals. The computational tools are costly, and the hospital also must pay to train and educate the cardiologists on the new tools (Lee et al., 2014).

To better understand how these computational tools can be integrated in hospitals, Actor-Network Theory (ANT) and Technological Momentum will be employed. ANT defines actors that are human and non-human entities that function as part of a complex network where each actor has unspecified relations with another (Cressman, 2009). The key actors in the integration of computational tools in cardiology include engineers, cardiologists, patients, hospital clinicians, hospital infrastructure, and the computational tools themselves. The overall networks in play are the research and development programs developing cardiac computational tools and the hospital workflow network. The intricate details of the computational tools will be black boxed to avoid convoluted analysis of what is "under the hood" of the tools such as algorithm structure. ANT will help define where modifications can be made from development to clinical use. There is some criticism of ANT that must be taken into consideration when conducting analyses. ANT fails to consider the social aspect of human considerations such as values and norms (Cressman, 2009). These factors are important in the development of computational tools so that the tools appeal to patients and cardiologists. Thus, another framework must be used in conjunction to help bridge the gap.

After understanding the actors present, technological momentum will be used to understand how clinical cardiology shapes new computational tools and vice versa. Technological momentum is described as the process where society's development shapes technology and technology itself shapes society's development simultaneously (Hughes, 1994). The framework will be used to understand how a cardiologist's and patient's need dictates what computational tools engineers must create. In addition, the opposite will be analyzed to see how engineers must modify computational tools so that they are usable by cardiologists. Technological momentum is time dependent where society generally starts with social determinism and then lends itself to technological determinism (Hughes, 1994). A critique of technological momentum is that it is difficult to know when technological determinism is activated. When analyzing how computational tools shape cardiology, it will be beneficial to know when technological determinism takes over. Consequently, not knowing the change from social determinism to technological determinism is a key limitation of the sociotechnical analysis.

Research Question and Methods

The research question is: how can cardiologists and engineers work together to increase the use of computational tools in routine clinical cardiology to aid in diagnoses and treatments of cardiovascular diseases? To answer the question, detailed solutions will be provided of how engineers can make their computational tools more accessible for cardiologists, and how cardiologists can adjust their workflow to increase the use of new computational tools.

Documentary research methods will be used to parse through published journal articles about what computational tools are present and/or in development in cardiology, what qualities are common among successful clinical computational tools, and what factors inhibit physicians and hospitals from adopting new technology in general. For instance, a case study analysis by Lapointe and Rivard 2006 looks at how the implementation of a new hospital computer information system and how physicians reacted to the new system (Lapointe & Rivard, 2006). Documentary analysis of the case study will provide information on what factors of new software implementation triggered physician resistance which will be extrapolated to computational tool integration with cardiologists. Network analysis will be used to understand how the hospital hierarchy functions when a new technology is adopted. Financial and organizational factors are key to determine what influences a hospital to accept new computational tools.

Lastly, brief interviews will be conducted with cardiologists at the University of Virginia Health System to understand what they are looking for in terms of adopting innovative computational tools. Interview questions will focus on what design and integration aspects of new technology physicians prefer. The questions will also focus on uncovering physicians' general opinions of new hospital technology. In addition, a portion of the questions will ask physicians about what they dislike about integrating new technology into their everyday workflow. The interviews will help bridge gaps between computational tool interfaces engineers build and interfaces cardiologists prefer. These three research methods will help shape what is needed to integrate computational tools in routine clinical cardiology. The three research methods will be employed during the spring of 2021.

Conclusion

For the technical portion of this portfolio, the research team will deliver working deep learning algorithms for medical image segmentation of coronary arteries, myocardial scarring in HCM patients, and ventricles in hydrocephalus patients. In addition, we will construct an intuitive software framework housing the algorithm for physician ease of use. The deep learning algorithms will be an improvement upon current automatic segmentation algorithms and will advance the diagnoses and treatments of coronary artery disease, HCM, and hydrocephalus. The algorithms will also help reduce inter-observer bias when analyzing medical images resulting in more consistent diagnoses and treatment plans. For the sociotechnical portion of this portfolio, I will deliver a detailed list of solutions to integrate computational tools in clinical cardiology. The detailed list will help engineers better tailor their computational tools for cardiologists which can help aid the clinical transition. The solution list will also help physicians become more active in accommodating new computational tools that have the potential to greatly better patient treatments.

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