Prospectus

Deep Learning for Automated Segmentation of Cardiac CT/MRI Images, as well as Cerebral CT Images.

(Technical Topic)

Exploring how Switching to Automated and AI Processes for Medical Diagnoses will Alter the Hospital-Physician System.

(STS Topic)

By

Rohan Patel

November, 5th, 2020

Technical Project Team Members:

Ramiz Akhtar, Vignesh Valaboju, Sharon Zheng

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.

Signed: _______Rohan Patel_________________
Technical Advisor: ____ Xue Feng____________________
STS Advisor: ___________Sean Ferguson_______

Introduction

In the modern medical age timely diagnosis of disease states are critical for effective treatment and healthy recovery of patients. Modern day physicians are subjected to scrupulous amounts of pressure to efficiently as well as accurately diagnose patients, while often given minimal information and time. In order to combat this issue, medical images from modalities such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) have become ubiquitous for preventative disease screening, disease diagnosis, and treatment selection for patients (Bercovich & Javitt, 2018). These images often undergo analysis through a process called manual segmentation, which differentiates anatomical regions of the image. The resulting images provide insurmountable qualitative and quantitative information for clinicians; however, the process of manual segmentation is an arduous and time-consuming task for physicians and often leads to inter-observer biases (Merjulah & Chandra, 2019).

The technical portion of the capstone uses deep learning convolutional neural networks (CNNs) to efficiently and consistently automate the manual segmentation process for three disease states: coronary artery disease, hypertrophic cardiomyopathy, and hydrocephalus. A CNN will be made for each respective disease state which will segment coronary arteries from Computed Tomography Angiographies (CTAs), myocardial scarring from MRIs of hypertrophic cardiomyopathy patients, and neural ventricles in CT scans of hydrocephalus patients. Although deep learning CNNs can be used to help aid physicians in quickly diagnosing disease states, there are often worries and trepidations when introducing automation into a pre-existing field like medicine, such as the fear of being replaced as well as the fear of exterminating human interaction (Huang & Rust, 2018). These worries often serve as barriers in implementing said technologies, which ultimately undermines the value and usefulness of the technology. Moreover, physician's acceptance has always played a role in hospitals adopting medical technologies, such as in the case with clinical information technologies, and experts posit automation in the medical field will be no different (Yarbrough & Smith, 2007). Thus, the sociotechnical portion of the capstone will analyze how switching to automated and deep learning processes for medical diagnoses can affect the physicians feeling of relevance, the patient-physician relationship, and how engineers can alter their design in order to gain physician's acceptance.

Technical Topic

In the clinical workflow, medical images such as CTs or magnetic MRIs are commonly used in diagnosis. Most current clinical processes rely on qualitative interpretation of the images by radiologists. However, quantitative evaluation can 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 of the image (Kim et al., 2015). We identify three disease states of interest that require 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 leading to a heart attack (Mayo Clinic, 2020). Coronary artery disease is the most common type of heart disease, killing 365,914 people in 2017, and affecting 18.2 million adults above the age of 20 in the United States (CDC, 2020). Current diagnosis of coronary artery disease mainly consists of manually segmenting CTAs for the presence of calcification and plaque residues (Arnett et al., 2019). This approach of identification is too time-consuming and inconsistent between users; however, through automated CTA segmentation, the narrowing and calcification of the coronary arteries can be quantified in a constant and timely manner, preventing heart attacks.

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 heart dysfunction (Kramer et al., 2015; Olivotto et al., 2011; Semsarian et al., 2015). Most HCM cases are genetically inherited and can gradually progress towards 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 left ventricular wall thickness and scarring (Wigle et al., 1985). Automating CMR image segmentation would allow for more efficient patient diagnosis and condition monitoring, ultimately improving personalized patient care.

Hydrocephalus affects 1 million people in the United States and it is very common in children as 1.1 in every 1000 infants will develop hydrocephalus (Tully & Dobyns, 2014). It is characterized by the buildup of fluid in the ventricles inside the brain which can damage brain tissues and cause severe disabilities (Hamilton et al., 2016). Image segmentation, an essential toolkit for hydrocephalus diagnosis, is used to extract snapshots of brain ventricles. Automating image segmentation can more efficiently estimate ventricular abnormality and can potentially distinguish between chronic and acute hydrocephalus, allowing physicians to optimize patient treatment plans.

Manual segmentation is currently used to diagnose all three of the disease states discussed above. Furthermore, manual segmentation is laborious and time consuming for physicians, and the process often leads to inter-observer biases resulting in inconsistent diagnoses (Merjulah & Chandra, 2019). Innovative automated processes are required for improved segmentation efficiency and consistency. There have been several recent advances in using artificial intelligence to automatically segment medical images (Litjens et al., 2017). Deep learning convolutional neural networks (CNNs) allow for image classification. Images can be fed through a series of convolutions to extract image features for classification. For segmentation, different regions of the images are classified. However, these attempts to use CNNs for segmentation often produce results far from satisfactory. For example, conventional CNN image segmentation algorithms used for coronary arteries show relatively limited performance with a Dice Similarity Coefficient (DSC) of 0.5975 and 0.66 (Kjerland, 2017; Moeskops et al., 2016). DSC is a statistic used to gauge the similarity of two segmentations, a DSC of 1 means the segmentations are identical. In image segmentation you are comparing the CNN algorithm segmentation from a "ground truth" which is an accurate manually segmented image.

The goal of the project is to **develop and validate more accurate, precise, and efficient deep learning-based segmentation algorithms for**

regions of interest for the three disease states in CT and MRI scans as well as implementing these algorithms into a medical software package. We plan on achieving this goal by adopting a fully convolutional neural network (FCNN). FCNNs have been leveraged for image segmentation since they take an image input and output an image or tensor (Maher et al., 2019). A specific type of FCNN is the UNet architecture which uses a series of downsampling convolutional layers and then a series of upsampling layers to reconstruct the segmented images (*U-Net — DeepLearning 0.1 Documentation*, n.d.). Each convolutional layer is followed by some form of normalization and an activation function. The downsampling layer encodes the image information and the upsampling layer decodes the classifications. UNet architecture is most common in medical imaging and has shown to provide a high DSC score for medical image segmentation (Liu et al., 2020). Medical images for each of the aforementioned disease states will be segmented for their regions of interest using a UNet backbone. For coronary artery segmentation, innovative multi-channel inputs about the prior shape of blood vessels will be fed into the FCNN to improve model result. 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 are done using MRIs; however, we will segment CT scans for increased spatial resolution. Automated segmentation results will be compared against the "ground truth" as a metric of success (DSC score).

Considering medical professionals must undertake a multitude of tasks, they must maintain high productivity when completing any given task. Presenting the aforementioned automated segmentation algorithms to physicians in their raw form would create potential for unintended modification of the algorithms, thus creating technical issues, reducing efficiency, and compromising patient care. To alleviate this concern, we also propose creating a universal software application to house and black-box our underlying automated segmentation algorithms. Creating a user interface (UI) that prioritizes simplicity, intuitive use, and extensive user control would grant 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 would make them more likely to see use in clinical and clinical training environments.

In order to complete the objectives of this project I will be working with Carina Medicals, a startup that originated from multiple labs at the University of Virginia and the University of Kentucky. Specifically, I will be working with three students from the University of Virginia, as well as Carina Medical Co-Founder, Dr. Xue Feng. My responsibility within this team is to help implement the tubular shape of the coronary arteries into Dr. Feng's pre-existing FCNN Coronary Artery segmentation algorithm in order to improve the accuracy, precision, and efficiency of the algorithm (Chen et al., 2019). I will be working with one other student on the Coronary Artery segmentation algorithm, while the other two students will be working on the goals stated for the HCM and hydrocephalus segmentation algorithms respectively. The resources required to complete this project consists of medical CT and MRI scans of patients with coronary artery disease, HCM, as well as hydrocephalus. These datasets originated from multiple hospital data records within

Virginia and Kentucky. Lastly, python tensor flow is used as the main software for the creation and manipulation of the FCNNs, while NVIDIA CUDA GPUs are used as the main computer systems to train and validate said FCNNs.

STS Topic

With the sudden boom of artificial intelligence from autonomous vehicles to autonomous factories, stakeholders in these respective fields are becoming more anxious and fearful for their occupations (Frank et al., 2019). The fact of the matter is that whenever automation and artificial intelligence is introduced into a new field of work questions about the intent of the technology arises. Such questions consist of "Is this technology meant for the augmentation of workers, or the replacement of workers?" or "How will this technology affect human interaction?". Artificial intelligence within the medical sector is no different, and physicians, patients, and clients all experience similar trepidations and worries about the intent of the technology (Ahuja, 2019). In addition, these trepidations serve as an impasse for implementing said technologies, resulting in the extermination of the value and potential relationship between the user and technology. Thus, my long-term objectives within this STS portion is to analyze how switching to deep learning and artificial intelligence for medical diagnoses will change the current regime of the hospital-physician system. Specifically, I will be looking at the physician's feeling of relevancy with AI, how the patient-physician relationship will be affected, and how creators of the technology can change their design in order to obtain the physician's trust and avoid an impasse situation.

Background Information and Framing

The hospital-physician system is one of the most unique systems seen within any sector or branch of society, and it is fundamentally driven through the sociotechnical interactions between physicians, clients, patients as well as medical tools or technologies. One staple of the hospital-physician system is the physician-patient relationship. In the most fundamental sense, the physician-patient relationship is defined as a consensual relationship in which the patient knowingly seeks the physician's assistance and in which the physician knowingly accepts the person as a patient. Within the physician-patient relationship there are four models which consists of the paternalistic model, the informative model, the interpretive model, and the deliberative model (Emanuel & Emanuel, 1992). Each model serves its own purpose to help provide the best course of action for the patient, for example, the deliberative model seeks to help the patient choose the best health related values by acting as a teacher or friend and engaging the patient in meaningful dialogue (Gedge & Waluchow, 2012). With the implementation of AI, stakeholders wonder what will remain of the physician-patient relationship. Debates about if artificial intelligence will help or harm the physician-patient system have been cited in numerous articles (Ahuja, 2019). Experts in medicine such as Abby Norman and Bertalan Meskó state how "your future doctor may not be human", and how AI is "The Stethoscope of the 21st Century" implying how doctors will likely be replaced, ending the physician-patient relationship (*Artificial Intelligence Is the Stethoscope of the 21st Century*, 2017; *Your Future Doctor May Not Be Human. This Is the Rise of AI in Medicine.*, n.d.). While other experts such as Krittanawong state how physicians are still needed for traditional physical exams, especially in areas such as neurology, which require high-level patient-physician interaction

(Krittanawong, 2018). Lastly, experts are also divided as to whether AI is likely to support and augment physicians by taking away the routine parts of a physician's work and enabling the physician to spend more time with their patients, or if the AI will take away all parts of the physician's work (Ahuja, 2019).

Another staple of the hospital-physician systems is the physicians-technology relationship or the physician's acceptance of technology. The physician's acceptance can be modeled by a technology acceptance model (TAM) (Chuttur, 2019). TAM serves to provide stakeholders a better understanding of physician technology acceptance, as well as inform stakeholders about barriers that make physicians hesitant to embrace new technologies designed to increase efficiency and improve quality in a health care setting (Yarbrough & Smith, 2007). Understanding the TAM model for artificial intelligence technologies can help give insight to the degree of AI implementation in the hospital-physician system, as well as helping understand how AI technologies affect a physician's feeling of relevancy, which are topics currently unknown and debated amongst medical professionals. Moreover, reverse engineering the TAM model can help aid engineers in designing technologies that will gain the trust of the physician, ultimately leading to a more productive society.

With the increasing implementation of automation and artificial intelligence into the medical fields many stakeholders are curious in how these staples of the hospital-patient system will be affected. Given that many experts are conflicted and confused about the stance of AI in the medical sector, exploration and analysis of this subject manner is necessary in order to obtain the true impact of AI in the medical sector as well as to prepare for the future of medicine.

Exploration of the Changes in the Medical Sector via Artificial Intelligence Through the Lens of Multi Level Perspective Theory

Multi-Level Perspective Theory (MLP), developed by Arie Rip and Rene Kemp, is a transitional framework that concerns itself with the way in how society and sociotechnical systems change and develop (Caletrío, 2015). MLP states how during a systems transformation three levels interact. These levels are classified at the regime level, the landscape level, and the niche level. The landscape refers to global or social trends that occur which influence and pressure the regime, the regime which is mainstream society that is supported by social norms and integrated systems, and the niche developments where new ideas are allowed to grow until they have an opportunity to challenge the existing regime (Geels & Schot, 2007). The changes within the hospital-physician system brought about niche developments in AI as well as landscape pressure to improve diagnostics can be observed through the lens of MLP.

I plan to use an altered version of MLP created by Geels & Schot, which acknowledges how different timing and nature of multi-level interactions lead to different outcomes. For example, if landscape pressure happens when niche-developments are not completed, the transition path will be different than when they are fully developed. In addition, Geels and Schot state that different multi-level interactions have natures associated with them, which also alter the transition path. For example, Niche-innovations have a competitive relationship with the existing regime, when they aim to replace it. Niche-innovations have symbiotic relationships if they can be adopted as enhancing add-ons in the existing regime. AI is a niche development that is still not fully developed, and has an unknown nature with the medical sector. In addition, the timing of the medical diagnosis in the medical field at the current moment is urgent, due to COVID-19 as well as everyone's concern for safety. Thus, this altered version of MLP will serve well in gaining insights.

Scope

Through the remaining time of this semester, as well as STS 4600, I will focus on how to use the altered MLP framework by Geels & Schot to examine how artificial intelligence and pressures for improved diagnostics will affect the hospital-physician system. Within the hospital-physician system, I will be focusing on the patient-physician relationship, the physician's feeling of relevancy, as well as how engineers can alter their designs to gain physician's acceptance. This will be done by expanding research on the regime level, landscape level, and the niche development level. I will also explore TAM to understand feelings of relevancy and optimal technology designs. For example, for the regime level I will do an extensive search on the current practices and standards of medical image diagnostics. For the landscape level, I will research the social pressures placed on hospitals in order to diagnose illnesses more accurately due to COVID-19. Lastly, for niche development, I will research the current state of AI in the medical field in order to understand its nature as well as its potential to infiltrate the regime. In addition, research will be conducted to help understand the controversies about AI, such as if AI is to augment or replace. Research will be conducted with academic sources, books, and trusted news articles since I consider these empirical sources of evidence. Once all the research is done, I will be able to map out how each level of MLP interacts with each other, thus being able to posit the changes in the medical sector via artificial intelligence. Lastly, the essential stakeholders are the physicians, patients, clients, institutions, as well as the engineers that are involved in innovation, implementation, or direct use of the medical system.

Next Steps

- November 4th – 15th: Obtain approval from STS professor on my prospectus.
- November 15th – 30th: Start the research process for the landscape level, as well as start working on the coronary artery UNET backbone.
- December 1st – 15th: Start the research process for the niche and regime level. Start looking at novel methods to increase efficiency, precision, and accuracy of the UNET algorithm.
- December 15th –31st: Start the research process on TAM, and how TAM can be used to support MLP and give insights on designing better technologies for physicians.
- February: Have a working coronary artery segmentation algorithm and start computing DSC scores with manual segmentations.
- March: Compile all my STS research in order to start "connecting dots" and witnessing the interactions between MLP levels.
- May: Submit Capstone paper, presentation as well as STS thesis.

References

Ahuja, A. S. (2019). The impact of artificial intelligence in medicine on the future role of the physician. *PeerJ*, *7*. https://doi.org/10.7717/peerj.7702

Arnett, D. K., Blumenthal, R. S., Albert, M. A., Buroker, A. B., Goldberger, Z. D., Hahn, E. J., Himmelfarb, C. D., Khera, A., Lloyd-Jones, D., McEvoy, J. W., Michos, E. D., Miedema, M. D., Muñoz, D., Smith, S. C., Virani, S. S., Williams, K. A., Yeboah, J., & Ziaeian, B. (2019). 2019 ACC/AHA Guideline on the Primary Prevention of Cardiovascular Disease: Executive Summary: A Report of the American College of Cardiology/American Heart Association Task Force on Clinical Practice Guidelines. *Circulation*, *140*(11). https://doi.org/10.1161/CIR.0000000000000677

Artificial Intelligence is the Stethoscope of the 21st Century. (2017, July 18). The Medical Futurist. https://medicalfuturist.com/ibm-watson-is-the-stethoscope-of-the-21st-century

Bercovich, E., & Javitt, M. C. (2018). Medical Imaging: From Roentgen to the Digital Revolution, and Beyond. *Rambam Maimonides Medical Journal*, *9*(4). https://doi.org/10.5041/RMMJ.10355

Caletrío, J. (2015). DEBATE Multi-Level Perspective and Theories of Practice: A mistaken controversy? *Mobile Lives Forum*.

CDC. (2020, September 8). *Heart Disease Facts | cdc.gov*. Centers for Disease Control and Prevention. https://www.cdc.gov/heartdisease/facts.htm

Chen, Y.-C., Lin, Y.-C., Wang, C.-P., Lee, C.-Y., Lee, W.-J., Wang, T.-D., & Chen, C.-M. (2019). Coronary Artery Segmentation in Cardiac CT Angiography

Using 3D Multi-Channel U-net. *ArXiv:1907.12246 [Eess]*. http://arxiv.org/abs/1907.12246

Chuttur, M. (n.d.). *Overview of the Technology Acceptance Model: Origins, Developments and Future Directions*. 24.

Collier, R. (2018). Rethinking EHR interfaces to reduce click fatigue and physician burnout. *CMAJ : Canadian Medical Association Journal*, *190*(33), E994–E995. https://doi.org/10.1503/cmaj.109-5644

Emanuel, E. J., & Emanuel, L. L. (1992). Four Models of the Physician-Patient Relationship. *JAMA*, *267*(16), 2221–2226. https://doi.org/10.1001/jama.1992.03480160079038

Frank, M. R., Autor, D., Bessen, J. E., Brynjolfsson, E., Cebrian, M., Deming, D. J., Feldman, M., Groh, M., Lobo, J., Moro, E., Wang, D., Youn, H., & Rahwan, I. (2019). Toward understanding the impact of artificial intelligence on labor. *Proceedings of the National Academy of Sciences of the United States of America*, *116*(14), 6531–6539. https://doi.org/10.1073/pnas.1900949116

Gedge, E. (Boetzkes), & Waluchow, W. J. (2012). *Readings in Health Care Ethics—Second Edition*. Broadview Press.

Geels, F. W., & Schot, J. (2007). Typology of sociotechnical transition pathways. *Research Policy*, *36*(3), 399–417. https://doi.org/10.1016/j.respol.2007.01.003

Hamilton, M., Gruen, J. P., & Luciano, M. G. (2016). Introduction: Adult hydrocephalus. *Neurosurgical Focus*, *41*(3), E1. https://doi.org/10.3171/2016.6.FOCUS16272

Huang, M.-H., & Rust, R. T. (2018). Artificial Intelligence in Service. *Journal of Service Research*, *21*(2), 155–172. https://doi.org/10.1177/1094670517752459

Kim, H., Park, C. M., Goo, J. M., Wildberger, J. E., & Kauczor, H.-U. (2015). Quantitative Computed Tomography Imaging Biomarkers in the Diagnosis and Management of Lung Cancer. *Investigative Radiology*, *50*(9), 571–583. https://doi.org/10.1097/RLI.0000000000000152

Kjerland, Ø. (2017). *Segmentation of Coronary Arteries from CT-scans of the heart using Deep Learning*. Undefined. /paper/Segmentation-of-Coronary-Arteries-from-CT-scans-of-Kjerland/e47be6bdca8af2a9f948128d6a1eabe99aa617eb

Kramer, C. M., Appelbaum, E., Desai, M. Y., Desvigne-Nickens, P., DiMarco, J. P., Friedrich, M. G., Geller, N., Heckler, S., Ho, C. Y., Jerosch-Herold, M., Ivey, E. A., Keleti, J., Kim, D.-Y., Kolm, P., Kwong, R. Y., Maron, M. S., Schulz-Menger, J., Piechnik, S., Watkins, H., … Neubauer, S. (2015). Hypertrophic Cardiomyopathy Registry (HCMR): The rationale and design of an international, observational study of hypertrophic cardiomyopathy. *American Heart Journal*, *170*(2), 223–230. https://doi.org/10.1016/j.ahj.2015.05.013

Krittanawong, C. (2018). The rise of artificial intelligence and the uncertain future for physicians. *European Journal of Internal Medicine*, *48*, e13–e14. https://doi.org/10.1016/j.ejim.2017.06.017

Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., van der Laak, J. A. W. M., van Ginneken, B., & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. *Medical Image Analysis*, *42*, 60–88. https://doi.org/10.1016/j.media.2017.07.005

Liu, L., Cheng, J., Quan, Q., Wu, F.-X., Wang, Y.-P., & Wang, J. (2020). A survey on U-shaped networks in medical image segmentations. *Neurocomputing*, *409*, 244–258. https://doi.org/10.1016/j.neucom.2020.05.070

Maher, G., Wilson, N., & Marsden, A. (2019). Accelerating cardiovascular model building with convolutional neural networks. *Medical & Biological Engineering & Computing*, *57*(10), 2319–2335. https://doi.org/10.1007/s11517-019-02029-3

Mayo Clinic. (2020, June 5). *Coronary artery disease—Symptoms and causes*. Mayo Clinic. https://www.mayoclinic.org/diseases-conditions/coronary-artery-disease/symptoms-causes/syc-20350613

Merjulah, R., & Chandra, J. (2019). Chapter 10—Classification of Myocardial Ischemia in Delayed Contrast Enhancement Using Machine Learning. In D. J. Hemanth, D. Gupta, & V. Emilia Balas (Eds.), *Intelligent Data Analysis for Biomedical Applications* (pp. 209–235). Academic Press. https://doi.org/10.1016/B978-0-12-815553-0.00011-2

Moeskops, P., Wolterink, J. M., van der Velden, B. H. M., Gilhuijs, K. G. A., Leiner, T., Viergever, M. A., & Išgum, I. (2016). Deep Learning for Multi-task Medical Image Segmentation in Multiple Modalities. In S. Ourselin, L. Joskowicz, M. R. Sabuncu, G. Unal, & W. Wells (Eds.), *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2016* (pp. 478–486). Springer International Publishing. https://doi.org/10.1007/978-3-319-46723-8_55

Olivotto, I., Girolami, F., Sciagrà, R., Ackerman, M. J., Sotgia, B., Bos, J. M., Nistri, S., Sgalambro, A., Grifoni, C., Torricelli, F., Camici, P. G., & Cecchi, F. (2011). Microvascular Function Is Selectively Impaired in Patients With

Hypertrophic Cardiomyopathy and Sarcomere Myofilament Gene Mutations. *Journal of the American College of Cardiology*, *58*(8), 839–848. https://doi.org/10.1016/j.jacc.2011.05.018

Semsarian, C., Ingles, J., Maron, M. S., & Maron, B. J. (2015). New Perspectives on the Prevalence of Hypertrophic Cardiomyopathy. *Journal of the American College of Cardiology*, *65*(12), 1249–1254. https://doi.org/10.1016/j.jacc.2015.01.019

Tully, H. M., & Dobyns, W. B. (2014). Infantile hydrocephalus: A review of epidemiology, classification and causes. *European Journal of Medical Genetics*, *57*(8), 359–368. https://doi.org/10.1016/j.ejmg.2014.06.002

U-Net—DeepLearning 0.1 documentation. (n.d.). Retrieved October 20, 2020, from http://deeplearning.net/tutorial/unet.html

Watkins, H., Ashrafian, H., & Redwood, C. (2011, April 27). *Inherited Cardiomyopathies* (world) [Review-article]. Http://Dx.Doi.Org/10.1056/NEJMra0902923; Massachusetts Medical Society. https://doi.org/10.1056/NEJMra0902923

Wigle, E. D., Sasson, Z., Henderson, M. A., Ruddy, T. D., Fulop, J., Rakowski, H., & Williams, W. G. (1985). Hypertrophic cardiomyopathy. The importance of the site and the extent of hypertrophy. A review. *Progress in Cardiovascular Diseases*, *28*(1), 1–83. https://doi.org/10.1016/0033-0620(85)90024-6

Yarbrough, A. K., & Smith, T. B. (2007). Technology acceptance among physicians: A new take on TAM. *Medical Care Research and Review: MCRR*, *64*(6), 650–672. https://doi.org/10.1177/1077558707305942

Your future doctor may not be human. This is the rise of AI in medicine. (n.d.). Futurism. Retrieved November 5, 2020, from https://futurism.com/ai-medicine-doctor