Development of Machine Learning Methods to Automate Image Segmentation of Mice Heart Ultrasound Images.

Accessibility of Robotic Assisted Gynecologic Surgery.

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By
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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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General Research Problem: Usage of Machine Learning Technology in Healthcare

How can machine learning be used in healthcare to improve patient outcomes and make decisions about diagnosis, treatment, and future prevention?

An important safety problem in healthcare is diagnostic error, with major errors being found in 10%-20% of autopsies (Saber et al., 2013). This suggests that an average of 60,000 patients die annually in the United States from error during diagnosis (Saber et al., 2013). Medical diagnosis is a critical task that must be performed efficiently and accurately to ensure adequate patient treatment. Factors including lack of communication, doctor inexperience, and lack of time with patients contribute to these errors (Balogh et al., 2015). With the complexity and rise of data in healthcare, machine learning (ML) technology has the potential to transform many aspects of patient care including diagnosing diseases (Davenport & Kalakota, 2019). There are studies suggesting that artificial intelligence (AI) can perform as well as or better than humans at key healthcare tasks such as identifying a malignant tumor (Davenport & Kalakota, 2019). Google's ML applications in healthcare detected breast cancer with 89% accuracy, which is an 11% increase compared to currently used diagnostic methods (Verma, V & Verma, S, 2022).

ML is a common form of AI that 'learns' by training models with data and can be used for tasks like personalized treatment, medical imaging, and robotic surgery (Kalaiselvi & Deepika, 2020). In 2021, about 90% of hospitals in the United States had some sort of AI strategy in place, with 75% of healthcare executives believing that AI initiatives are crucial for hospital success (Kent, 2021). However, out of that 90%, only 33% of hospitals had systems past the pilot stage in place due to lack of infrastructure or financial means (Kent, 2021). Lack of access to certain AI technologies, such as robotic surgical systems, may be detrimental to hospitals and patients seeking treatment. Automated medical imaging, a type of AI technology, is becoming more common since it is cost-effective for hospitals (Verma, V & Verma, S, 2022). Thus, the focus of this project is to develop a ML model for automated imaging of the heart. However, access to robotic surgery, another type of AI technology, varies greatly between hospitals. Therefore, the disparity in access to robotic surgery technology between demographic groups in the United States will be analyzed to discuss the need for stronger robotic surgery initiatives in hospitals.

Development of Machine Learning Methods to Automate Image Segmentation of Mice Heart Ultrasound Images.

How can deep learning models be used to quantitatively identify and classify heart dysfunction in mice post heart attack?

In the United States, a heart attack occurs every 40 seconds, and accurate cardiac imaging is crucial to prevent misdiagnosis and ensure proper treatment (Ouyang et al., 2020). An important step in cardiac imaging is segmentation. Medical image segmentation involves partitioning image data and identifying specific regions of interest. In medical images such as CTs or MRIs, this involves identifying the pixels of specific organs or lesions (Hesamian et al., 2019). Numerous image segmentation methods have been developed in the past, including manual (slice by slice) and semi-automatic segmentation. However, these methods are variable, time consuming and susceptible to error (Hesamian et al., 2019). Automatic segmentation has the potential to extract information from large amounts of medical image data with increased quality, accuracy, and decreased computation time (Ouyang et al., 2020). Recently, automatic segmentation methods using deep-learning models, a type of ML that mimics the human brain, have been developed to classify heart failure (Ouyang et al., 2020). However, these models had a significant error rate when classifying heart failure (Ouyang et al., 2020). To address the shortcomings of previous models, this project will focus on developing a deep learning model for automated image segmentation of heart ultrasound images in mice post myocardial infarction (MI), also known as a heart attack. My partner and I will then use machine learning techniques to improve accuracy of the model and identify heart dysfunction in mice using relevant physiological metrics such as heart wall thickness, ejection fraction (the heart's ability to pump blood), and cardiac contractility (the heart's ability to contract).

Data to develop the model will be extracted from videos of mice echocardiographs prior to and after administration of iNOS, a medicine which induces heart attack in mice. Ground truth labeling with the appropriate tools will be performed once frames are extracted to use as part of training and testing image sets required for model development. One constraint anticipated is varied image quality. Motion correction methods and noise filters will be used to remove noise and other artifacts to enhance image quality. Once data is collected and prepared, existing and novel deep learning algorithms will be combined to automate image segmentation and identification of the inner left ventricle heart wall. After identifying the heart wall, the thickness will be measured. Using mathematical equations for mice, wall thickness will be used to quantify physiological measurements relevant to heart failure such as ejection fraction and cardiac contractility (Gao et al., 2011). Heart failure is classified if values of ejection fraction and cardiac contractility are below a certain threshold. U-net architecture, a type of deep learning model, will be utilized since it was created specifically for biomedical image segmentation and has strong performance across a range of segmentation applications (Seo et al., 2020). Once developed, the model will be optimized and applied to quantify and classify heart dysfunction. To demonstrate that the model is more accurate than existing segmentation methods, the model will be applied to extracted data to measure heart dysfunction in mice. ML techniques will be used to optimize the model, and accuracy will be confirmed through comparison with manually segmented images (Kingma & Ba 2017).

Although the results collected will be based on mice data, human and mice imaging have many similarities, and this model has the potential to be used for human applications. This project aims to develop an effective image segmentation model with increased accuracy and speed for identifying heart dysfunction post MI in mice. This model will aid continuing research applications, as mice are commonly used animal models of cardiac failure. Cardiovascular changes in humans and mice are comparable post MI; thus, this model can be applied to quantify heart dysfunction in humans. This model could allow for reduced time in analyzing imaging data and ultimately improve patient outcomes by contributing to research, diagnosis, and treatment of cardiovascular diseases.

Accessibility of Robotic Assisted Gynecologic Surgery.

How does access to robotic assisted gynecologic surgery differ between demographic groups in the United States?

Robotic assisted (RA) surgery allows doctors to perform complex procedures with increased precision, flexibility, and control compared to traditional techniques. The surgeon can control robotic arms while seated at a computer console in the operating room, allowing them to have a magnified, 3D view of the surgical site (Terra et al., 2021). In the United States, the primary surgical robot used is the DaVinci surgical system which was first introduced in gynecologic surgery in 2005. Patients undergoing gynecologic surgery may benefit from a robotic approach due to shorter operating time, decreased blood loss during surgery, and shorter hospital stay compared to other methods. RA surgery has also been found to result in decreased postoperative complications, and earlier return to everyday activities (Varghese et al., 2019). More recently, there has been exploration in gynecologic surgery surrounding the incorporation of machine learning in surgery, enabling real-time observance and direct feedback on surgical performance. This improves the ability of repetitive accuracy and overcomes human limitations such as fatigue and emotional state (Bozkurt et al., 2022). Due to these benefits, patients undergoing gynecologic surgery should have access to robotic technology.

Robotics in Gynecologic Surgery

There was significant skepticism surrounding RA surgery when it was introduced; however, the use of robotics in gynecologic surgery is increasing in the United States for procedures such as hysterectomies (removal of the uterus) (Varghese et al., 2019). Hysterectomies are the most frequently performed major gynecologic surgery in women, with more than 400,000 procedures being performed in the United States. In 2002, the traditional abdominal approach accounted for 69% of hysterectomies. By 2016, robotic approaches accounted for 56% of hysterectomies, signifying a trend towards minimally invasive robotic surgery (Barnes et al., 2021). Hospital acquisition of robotic surgery equipment and aggressive marketing about new technology has resulted in increased patient demand for robotic surgery. However, major obstacles to the widespread acceptance of RA gynecologic surgery are skepticism towards robots in surgery, a steep learning curve for surgeons and cost to hospitals (Varghese et al., 2019). Certain racial and socioeconomic groups with gynecologic cancer are less likely to receive the option to undergo robotic surgery, which has been shown to have benefits over traditional methods (Barnes et al., 2021). It is concerning that certain demographic and patient groups are facing barriers to treatment and better outcomes.

Disparities in Patients Undergoing Gynecologic Surgery

Literature suggests that access to gynecologic robotic surgery varies by race and socioeconomic status. A study concluded that African American women are 10% and Hispanic women are 5% less likely to receive a RA surgery compared to white women (Pollack et al., 2020). There is data to suggest that hospitals in lower income zip codes are less likely to offer the option of robotic surgery. Insurance status may also impact the type of surgery done, as individuals with private health insurance compared to Medicaid have higher odds of being treated at hospitals with robotic surgery. In addition, teaching hospitals and hospitals located in urban regions were found more likely to offer robotic surgery for patients undergoing gynecologic surgery (Barnes et al., 2021). In many cases, the traditional (non-robotic) approach was used due to complex patient pathology, lack of robotic equipment, and the surgeons lack of experience. These differences in treatment type can lead to disparities in hysterectomy outcomes since RA hysterectomies have shown to produce more successful results (Mohanty et al., 2022). Disparities in access to RA gynecologic surgery, more specifically hysterectomies, can be further analyzed using case studies.

Numerous case studies have been conducted that focus on disparities in surgical care among women undergoing hysterectomies. These studies are typically done as a cohort over the span of a few years with hysterectomy patient data taken from specific care centers or the National Inpatient Sample database (Pollack et al., 2020). The case studies researched will capture a range of perspectives and will provide the opportunity to gain a deeper understanding of the problem. These studies can help identify inequalities in surgical care by providing data on factors including patient race and socioeconomic status. They also include data for factors such as cost of surgery, hospital size, teaching status, and geographic location that can contribute to disparities in access to RA hysterectomies (Mannschreck et al., 2016). The data and information from the case studies will be synthesized to determine how different groups have interacted with RA surgery. The case studies will also be compared to provide new analysis on what factors and challenges certain groups face in terms of accessibility to RA surgery. From the case studies, quantitative evidence from hospitals who use RA surgery will be collected and compared with hospitals that utilize traditional methods. Comparison between data such as adverse events during surgery and surgical outcomes for both RA surgery and traditional methods can be used to demonstrate the differences in access to robotic surgery. Certain case studies also have qualitative data which includes first-hand accounts from patients undergoing gynecologic surgery (Pollack et al., 2020). This data can be used to determine how often different demographic groups choose not to have RA surgery even when given the opportunity, and if patients have felt as though they have suffered because they did not have access to RA surgery. The case studies and data provided will be analyzed to discuss the need for robotic surgery initiatives in hospitals that currently do not utilize robotic technology.

Conclusion

This project will provide an analysis of the differences in access to RA hysterectomies between demographic groups in the United States and the potential need for robotic surgery initiatives in hospitals. Robotic surgical technology in gynecology has been shown to have many advantages over traditional methods including better patient outcomes (Barnes et al., 2021). With the increasing incorporation of machine learning into surgical technology and healthcare overall, accurate machine learning models and techniques are needed for patient treatment. The development of a model through this project will enable the identification of heart dysfunction post heart attack. This can used to improve outcomes of patients with cardiovascular diseases. Patient access to both machine learning and robotic surgical technology may be critical to further improve patient outcomes and make accurate decisions about diagnosis, treatment, and future prevention.

References

Balogh, E. P., Miller, B. T., Ball, J. R., Care, C. on D. E. in H., Services, B. on H. C., Medicine, I. of, & The National Academies of Sciences, E. (2015). Overview of Diagnostic Error in Health Care. In *Improving Diagnosis in Health Care*. National Academies Press (US). https://nap.nationalacademies.org/

Barnes, W. A., Carter-Brooks, C. M., Wu, C. Z., Acosta, D. A., & Vargas, M. V. (2021). Racial and ethnic disparities in access to minimally invasive gynecologic surgery for benign pathology. *Current Opinion in Obstetrics and Gynecology*, *33*(4), 279–287. https://doi.org/10.1097/GCO.0000000000000719

Bozkurt, E., Sijberden, J. P., & Hilal, M. A. (2022). What Is the Current Role and What Are the Prospects of the Robotic Approach in Liver Surgery? *Cancers*, *14*(17), Article 17. https://doi.org/10.3390/cancers14174268

Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. *Future healthcare journal*, *6*(2), 94–98. https://doi.org/10.7861/futurehosp.6-2-94

Gao, S., Ho, D., Vatner, D. E., & Vatner, S. F. (2011). Echocardiography in Mice. *Current Protocols in Mouse Biology*, *1*(1), 71–83. https://doi.org/10.1002/9780470942390.mo100130

Hesamian, M. H., Jia, W., He, X., & Kennedy, P. (2019). Deep Learning Techniques for Medical Image Segmentation: Achievements and Challenges. *Journal of Digital Imaging*, *32*(4), 582–596. https://doi.org/10.1007/s10278-019-00227-x

Kalaiselvi, K., & Deepika, M. (2020). Machine Learning for Healthcare Diagnostics. In V. Jain

& J. M. Chatterjee (Eds.), *Machine Learning with Health Care Perspective: Machine Learning and Healthcare* (pp. 91–105). Springer International Publishing. https://doi.org/10.1007/978-3-030-40850-3_5

Kent, Jessica. (2021). *90% of Hospitals Have Artificial Intelligence Strategies in Place*. HealthITAnalytics. https://healthitanalytics.com/news/90-of-hospitals-have-artificial-intelligence-strategies-in-place

Kingma, D. P., & Ba, J. (2017). *Adam: A Method for Stochastic Optimization* (arXiv:1412.6980). arXiv. https://doi.org/10.48550/arXiv.1412.6980

Mannschreck, D., Matsuno, R. K., Moriarty, J. P., Borah, B. J., Dowdy, S. C., Tanner, E. J. I., Makary, M. A., Stone, R. L., Levinson, K. L., Temkin, S. M., & Fader, A. N. (2016). Disparities in Surgical Care Among Women With Endometrial Cancer. *Obstetrics & Gynecology*, *128*(3), 526–534. https://doi.org/10.1097/AOG.0000000000001567

Mohanty, A., Lombardo, A. M., Judge, C., & Gundeti, M. S. (2022). Are there disparities in access to robot-assisted laparoscopic surgery among pediatric urology patients? US institutional experience. *International Journal of Urology*, *29*(7), 661–666. https://doi.org/10.1111/iju.14866

Ouyang, D., He, B., Ghorbani, A. *et al.* Video-based AI for beat-to-beat assessment of cardiac function. *Nature* 580, 252–256 (2020). https://doi.org/10.1038/s41586-020-2145-8

Pollack, L. M., Olsen, M. A., Gehlert, S. J., Chang, S.-H., & Lowder, J. L. (2020). Racial/Ethnic Disparities/Differences in Hysterectomy Route in Women Likely Eligible for Minimally Invasive Surgery. *Journal of Minimally Invasive Gynecology*, *27*(5), 1167-1177.e2. https://doi.org/10.1016/j.jmig.2019.09.003

Saber Tehrani, A. S., Lee, H., Mathews, S. C., Shore, A., Makary, M. A., Pronovost, P. J., & Newman-Toker, D. E. (2013). 25-Year summary of US malpractice claims for diagnostic errors 1986-2010: an analysis from the National Practitioner Data Bank. *BMJ quality & safety*, *22*(8), 672–680. https://doi.org/10.1136/bmjqs-2012-001550

Seo, H., Badiei Khuzani, M., Vasudevan, V., Huang, C., Ren, H., Xiao, R., Jia, X., & Xing, L. (2020). Machine learning techniques for biomedical image segmentation: An overview of technical aspects and introduction to state-of-art applications. *Medical Physics*, *47*(5), e148–e167. https://doi.org/10.1002/mp.13649

Terra, R. M., Leite, P. H. C., & Dela Vega, A. J. M. (2021). Global status of the robotic thoracic surgery. *Journal of Thoracic Disease, 13*(10), 6123–6128. https://doi.org/10.21037/jtd-19-3271

Varghese, A., Doglioli, M., & Fader, A. N. (2019). Updates and Controversies of Robotic-Assisted Surgery in Gynecologic Surgery. *Clinical obstetrics and gynecology*, *62*(4), 733–748. https://doi.org/10.1097/GRF.0000000000000489

Verma, V. K., & Verma, S. (2022). Machine learning applications in healthcare sector: An overview. *Materials Today: Proceedings*, *57*, 2144–2147. https://doi.org/10.1016/j.matpr.2021.12.101