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X-ray and CT Medical Images Segmentation

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Internship Report

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Resumo

Os avanços na imagiologia médica têm um papel fundamental na melhoria dos diagnósticos e tratamentos de saúde, proporcionando imagens detalhadas das estruturas internas do corpo humano. Entre os métodos mais utilizados estão as radiografias convencionais (raios-X) e as tomografias computadorizadas (TAC), cada uma com suas próprias características e aplicações clínicas.

As radiografias convencionais são amplamente usadas para visualizar a estrutura óssea e identificar fraturas ou outras anomalias. As tomografias computadorizadas, por sua vez, oferecem uma visão tridimensional das estruturas internas, permitindo uma análise mais aprofundada e detalhada das condições médicas. Ambos os tipos de imagens são essenciais em diagnósticos médicos e requerem técnicas específicas para a segmentação precisa das áreas de interesse.

A segmentação de imagens médicas, que consiste na separação das diferentes estruturas dentro de uma imagem, é uma etapa crítica para a análise e interpretação correta dos dados da mesma. Na última década, as técnicas mais utilizadas nesta área têm levado a um desperdício anual de milhares de milhões de euros em implantes que não são utilizados, principalmente devido ao subdesenvolvimento das etapas pré-cirurgia. Com os desenvolvimentos tecnológicos mais recentes, nasceu a hipótese de desenvolver modelos de inteligência artificial (IA) capazes de automatizar a segmentação, melhorando a precisão, eficiência e capacidade de processamento dos diagnósticos. Além de economizar recursos, esses modelos também poupam até 20% do tempo necessário para a realização dos procedimentos, representando um avanço significativo tanto em termos económicos quanto operacionais na área médica.

Uma vez que os modelos de IA requerem um treino inicial onde recebem muitos dados classificados, é necessário pré-processar e classificar estes dados. Neste contexto, foram utilizadas técnicas de segmentação manual e semiautomática para preparar conjuntos de dados de imagens de raios-X e TAC, possibilitando treinar um modelo de IA que futuramente será capaz de realizar segmentações automaticamente, facilitando o trabalho dos profissionais de saúde e melhorando os resultados clínicos.

A importância deste trabalho é igualmente evidenciada pela sua contribuição direta para os Objetivos de Desenvolvimento Sustentável (ODS), especialmente na melhoria da saúde e bem-estar (ODS 3), crescimento económico (ODS 8), inovação (ODS 9), redução das desigualdades (ODS 10) e consumo e produção responsáveis (ODS 12).

A experiência proporcionada por este estágio demonstra que a segmentação de imagens médicas, apesar do seu notável percurso evolutivo, continua a constituir um empreendimento trabalhoso e demorado. Consequentemente, é de salientar o potencial positivo que a adoção de métodos avançados de segmentação, aliada ao desenvolvimento de modelos de IA, representa em direção a diagnósticos mais rápidos e precisos, melhorando significativamente a qualidade do atendimento ao paciente e a eficiência dos sistemas de saúde.

Palavras-chave: segmentação de imagens médicas, radiografias, tomografias computadorizadas, inteligência artificial, ODS

Abstract

Advances in medical imaging play a fundamental role in improving diagnoses and treatments, providing detailed images of the internal structures of the human body. Amongst the most used methods are conventional radiography (X-rays) and computed tomography (CT), each with its own characteristics and clinical applications.

Conventional radiography is widely used to visualize bone structures and identify fractures or other anomalies. Computed tomography, on the other hand, offers a three-dimensional view of internal structures, allowing for a more in-depth and detailed analysis of medical conditions. Both types of images are essential in medical diagnostics and require specific techniques for precise segmentation of the areas of interest.

Medical image segmentation, which involves the separation of different structures within an image, is a critical step for the correct analysis and interpretation of image data. In the past decade, the most used techniques in this area have led to an annual waste of billions of euros in unused implants, primarily due to underdeveloped pre-surgery stages. With recent technological developments, the hypothesis of developing artificial intelligence (AI) models capable of automating segmentation has emerged, improving the accuracy, efficiency, and processing capacity of diagnostics. In addition to saving resources, these models also save up to 20% of the time required to perform procedures, representing a significant advancement both economically and operationally in the medical field.

Since AI models require initial training where they receive a lot of classified data, it is necessary to pre-process and classify this data. In this context, manual and semi-automatic segmentation techniques were used to prepare datasets of X-ray and CT images, making feasible the training of an AI model that will perform segmentations automatically in the future, facilitating the work of healthcare professionals and improving clinical outcomes.

The importance of this work is equally evidenced by its direct contribution to the Sustainable Development Goals (SDGs), particularly in improving health and well-being (SDG 3), promoting economic growth (SDG 8), fostering innovation (SDG 9), reducing inequalities (SDG 10) and encouraging responsible consumption and production (SDG 12).

The experience provided by this internship demonstrates that medical image segmentation, despite its notable evolutionary path, continues to be a laborious and time-consuming endeavor; consequently, the potential positive impact of adopting advanced segmentation methods, combined with the development of AI models, cannot be overstated. These advancements lead to faster and more accurate diagnoses, significantly improving the quality of patient care and the efficiency of healthcare systems.

Keywords: medical image segmentation, radiography, computed tomography, artificial intelligence, SDGs

1. Introduction

Image segmentation is a critical process in the field of computer vision and medical imaging. It involves partitioning an image into multiple segments or regions [1] to simplify its representation and make it more meaningful for analysis. This process is essential in various applications, including object detection, image recognition, and, notably, medical diagnostics. Image segmentation methods began with very rudimentary techniques but driven by the need for greater precision and efficiency they have evolved, with the most significant advances in recent decades. Now, in addition to the initial fully manual method, there are semi-automated or even fully automated techniques for segmenting medical images. These include techniques that use threshold, edge detection, region-based, clustering and machine learning.

1. *Early Methods of Image Segmentation*

The earliest methods of image segmentation were largely manual, requiring significant human effort to delineate regions of interest within an image. These techniques, though accurate, were labor-intensive and time-consuming [3], limiting their practical application in large-scale tasks. Manual segmentation involves drawing boundaries around objects of interest directly on the image, which requires an experienced operator for best results, is highly subjective and prone to variability between different operators [3].

2. *Thresholding Techniques*

One of the foundational techniques that emerged to automate the segmentation process was thresholding. Thresholding methods segment an image by converting it into a binary image, where the pixels are classified into object and background based on a chosen intensity threshold. This method is simple and computationally efficient but struggles with images where object and background intensities overlap or vary significantly [4].

There are essentially two types of this technique:

1. **Global Thresholding**: Uses a single threshold value for the entire image. This method works well for images with clear, uniform contrast between objects and the background [1].
2. **Adaptive Thresholding**: Applies different thresholds to different regions of the image. This technique is useful for images with varying lighting conditions but can be more complex and computationally demanding [1].

3. *Edge Detection*

Edge detection methods aim to identify the boundaries of objects within an image: by detecting discontinuities in image intensity, these methods can outline the shapes of objects. Popular edge detection algorithms include the Sobel, Canny, and Laplacian operators. Edge detection is particularly useful in identifying well-defined structures but can be sensitive to noise and may struggle with objects that do not have clear edges [5].

Region-based segmentation methods focus on partitioning the image into regions that are similar according to a set of predefined criteria. There are two main types of this technique: region growing and region splitting and merging.

1. **Region Growing**: Initiates from seed points and grows regions by appending neighboring pixels that have similar properties/meet certain criteria. This method is straightforward but sensitive to the choice of seed points and similarity criteria, so sometimes leads to over-segmentation [5].
2. **Region Splitting and Merging**: Splits the image into smaller regions and then merges them based on similarity criteria. This method balances the granularity of segmentation and helps to avoid over -segmentation.

4. *Clustering Methods*

Clustering techniques, such as k-means and fuzzy c-means, group pixels into clusters based on their features (e.g., intensity, color). These methods treat segmentation as a clustering problem where the image is partitioned into clusters representing different regions. Clustering methods can handle more complex images but may require more computational resources and careful tuning of parameters [5].

Model-Based and Machine Learning Approaches

In recent years, the introduction of machine learning and deep learning techniques has revolutionized image segmentation. Convolutional neural networks (CNNs), particularly, have shown remarkable performance in segmenting complex images with high accuracy [2]. These models are trained on large datasets and can learn to recognize intricate patterns and structures within images. These techniques include:

1. **Convolutional Neural Networks (CNNs)**: Deep learning models that have proven highly effective in image segmentation tasks [2]. They can automatically learn features from data, reducing the need for manual feature engineering.
2. **U-Net and Variants**: Specific architectures designed for biomedical image segmentation, known for their ability to produce precise segmentations with relatively small amounts of training data [2].

Methods Employed in This Work

The work described in this report employed a sequential approach to segmentation techniques, over the course of the internship. During the first few weeks, manual segmentation was solely utilized, allowing myself to become acquainted with image segmentation and being able to learn how to properly perform a manual segmentation on the single image x-rays, CRs, ensuring that the regions of interest were accurately delineated. In the subsequent weeks, I was taught how to apply region growing methods to CT images, which constituted a shock in comparison to fully manual segmentation. Finally, in the last weeks of the internship, multilevel thresholding was introduced for CT images, thus further refining the segmentation process, allowing for more precise separation of different regions within the images. This progression of techniques provided a comprehensive comparison of their effectiveness and adaptability to different types of medical images.

The evolution from manual segmentation to advanced techniques like region growing and multilevel thresholding reflects the ongoing advancements in the field of image segmentation, aiming to improve both the accuracy and efficiency of medical image analysis. These methods collectively contribute to the development of robust models capable of automating the segmentation process, thus enhancing diagnostic capabilities and clinical outcomes [2].

2. Internship Objectives

In this chapter, the internship objectives will be categorized and briefly explained, since further development will take place in chapter 3.

2.1. Manual x-ray segmentation with ITK-snap

As it was mentioned, the first weeks of the internship were dedicated to manual segmentation on x-ray images, which was conducted by resourcing to the ITK-SNAP software.

ITK-SNAP [7] is a software application widely used for the segmentation of 3D medical images. It provides an intuitive interface with interactive tools, including real-time image navigation and semi-automatic segmentation capabilities, which enhance the efficiency and accuracy of segmentation tasks. This software is particularly valued for its compatibility with various image formats and its integration with other imaging software, making it a versatile tool in medical imaging research and clinical practice. Notably, it offers robust manual segmentation features, allowing users to delineate structures within medical images with high precision.

2.2. Region growing segmentation with ITK-snap

After the first contact with manual segmentation, the new objective became being able to perform segmentation in more complex forms of medical images, such as CTs. For that end, the region growing method in ITK-snap was introduced, which allows to simultaneously segment the hundreds of images contained within one single CT image; afterwards, it´s always necessary to complement the work performed with the region growing method, since despite being an extremely helpful tool it still needs final manual adjustments, therefore being considered a semi-automated segmentation method.

As previously introduced, region growing is a segmentation technique that starts with seed points and expands regions by appending neighboring pixels that meet specific similarity criteria [1], as previously discussed. ITK-SNAP is particularly well-suited for this method due to its interactive interface and robust region growing tools. The software allows users to easily select seed points and adjust the criteria for region expansion, providing real-time feedback and visualization. This makes ITK-SNAP an efficient and user-friendly tool for implementing region growing, ensuring accurate and consistent segmentation results.

2.3. Multilevel thresholding with 3D-Slicer

Finally, to further enhance the learning process, the 3D slicer software was used, using the multilevel thresholding tool, among others.

Multilevel thresholding is an advanced image segmentation technique that extends the concept of basic thresholding by using multiple threshold values to partition an image into several segments. This method is particularly advantageous for segmenting complex images with varying intensities, as it allows for more precise differentiation of regions compared to single threshold methods [6].

3D Slicer [8] is a versatile, open-source software platform designed for the analysis and visualization of medical images. It offers a comprehensive suite of tools for image processing, including support for multilevel thresholding, 3D visualization, and a wide range of other segmentation methods. 3D Slicer is also known for its extensibility, allowing users to customize and extend its functionality through plugins and scripting.

This software is especially suitable for multilevel thresholding due to its robust image processing capabilities and user-friendly interface. The ability to handle multiple thresholds seamlessly within 3D Slicer ensures precise and efficient segmentation of complex medical images, making it an invaluable tool for researchers and clinicians aiming to achieve detailed and accurate image analysis.

3. Results and progress description

3.1. Initial stage

The first week of the internship was designed to be an accessible introduction to the tasks and tools that would be utilized throughout the project. This initial period was crucial in allowing me to gain confidence and become well-acquainted with the software and methodologies I would be using, after receiving a training tutorial provided by the team who supervised me.

During this time, I focused on understanding the basic functionalities of ITK-SNAP. The accessible nature of the initial tasks provided a solid foundation for building my skills. I spent this week exploring the user interfaces and practicing manual segmentation techniques.

A gradual introduction was essential to ensure that I was well-prepared for the more complex segmentation tasks that would follow. By the end of the first week, I had realized the difficulty of the task at hand, since I found too arbitrary to manually draw the line that establishes the bones´ boundaries, for not only it is often hard to identify as it appears dependent on the present image contrast; furthermore, I found the work to be extremely tiresome and somewhat frustrating, in addition to the lack of dynamic inherent to the task itself.

Here are some of the very first segmentations I performed:

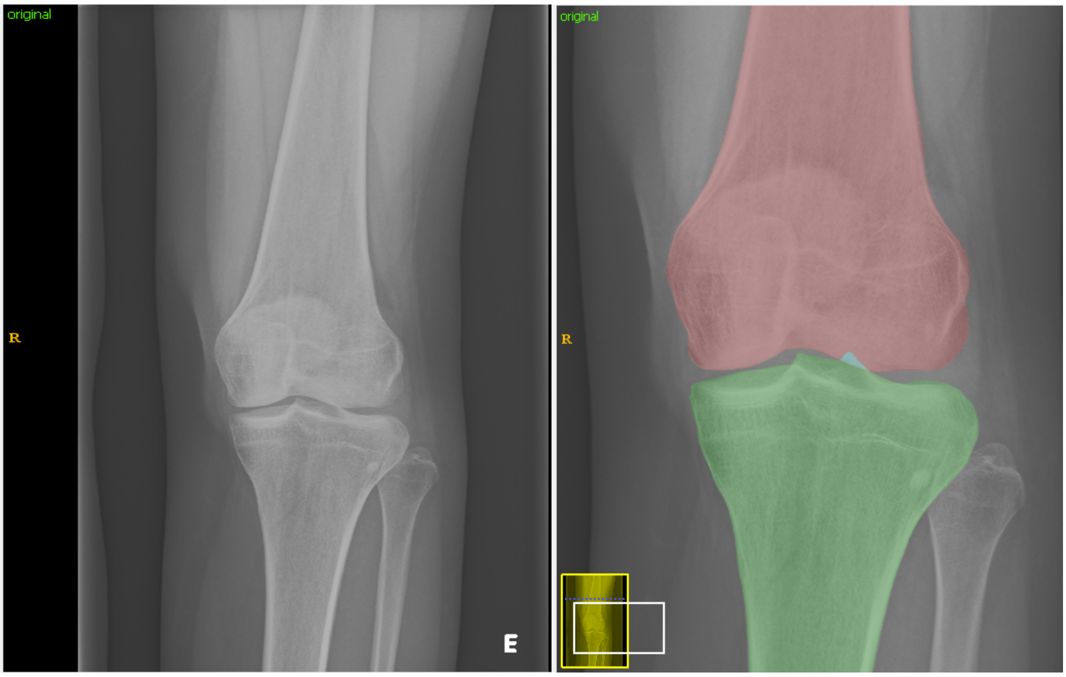

Figure 1. Knee APCR Segmentation performed using ITK-SNAP software. (1A. Image without segmentation. 1B. Image with the segmentation of 2 bones: femur (red), tibia (green) and the intersection of the two (blue)

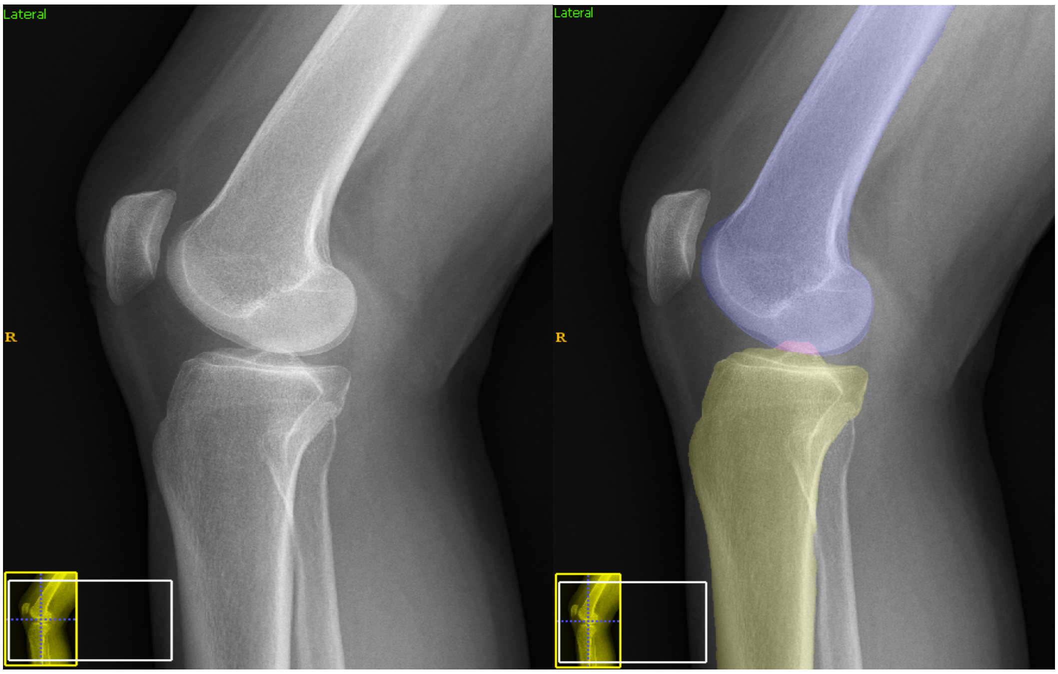

Figure 2. Knee LatCR Segmentation performed using ITK-SNAP software. (1A. Image without segmentation. 1B. Image with the segmentation of 2 bones: femur (blue), tibia (yellow), and the intersection of the two (pink)

After this first initial contact, I managed to get in touch with the team I was working with, in order to clarify the segmentation criteria and get feedback on my previous work. I found this to be extremely helpful, since they not only encouraged me by providing helpful tips, understanding and positive reviews to my former work, as they also cultivated a very open and friendly working environment, putting me at ease.

What follows are some of the segmentations I performed during the following weeks, regarding also a different anatomical area (pelvis) and including more anatomical components as part of the segmentation. At this stage, the supervisors believed I was ready to complement my work with the previous knee images, so additionally to segmenting the femur and tibia in the knee images, I also segmented the patella and fibula (figure 3). This work took me considerably more time than the previous knee images. I believe the biggest difficulty was identifying the contour of the patella, for even by changing contrast the difference between the bones can be practically null.

Regarding the pelvis x-ray images (figures 4 and 5), these images took me well over an hour to complete the segmentation. I found it interesting to segment specially the head of the femur area, for it is well visible and "logical", if this is understandable. One of the easements I encountered was the fact that on some of the images there were lead shield protectors that sometimes were overlapping with some parts of the bone(s), preventing me from segmenting the intersection with the sacrum, which I found to be the hardest part (figure 5).

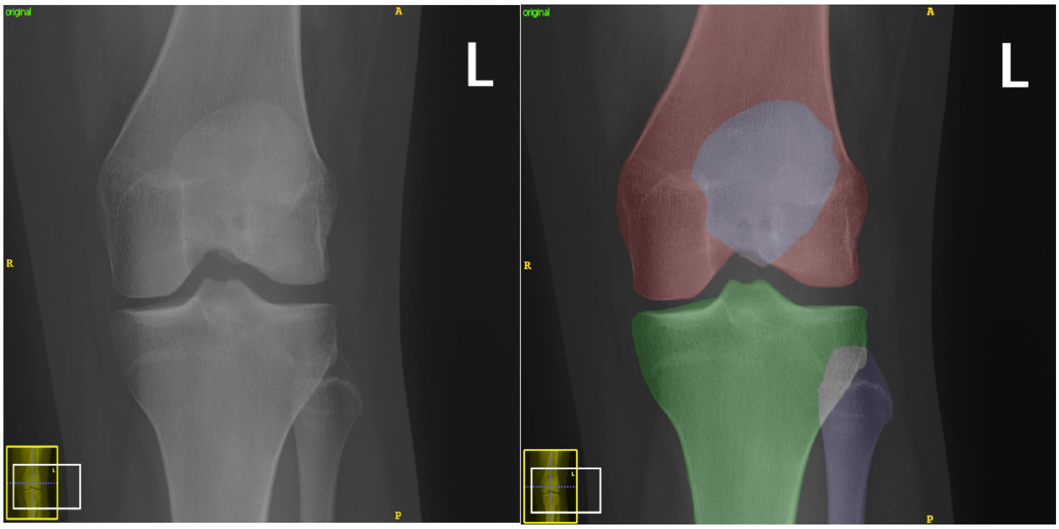

Figure 3. Knee APCR Segmentation performed using ITK-SNAP software. (1A. Image without segmentation. 1B. Image with the segmentation of 4 bones: femur (red), tibia (green), fibula (dark purple), patella (light purple), and various intersections

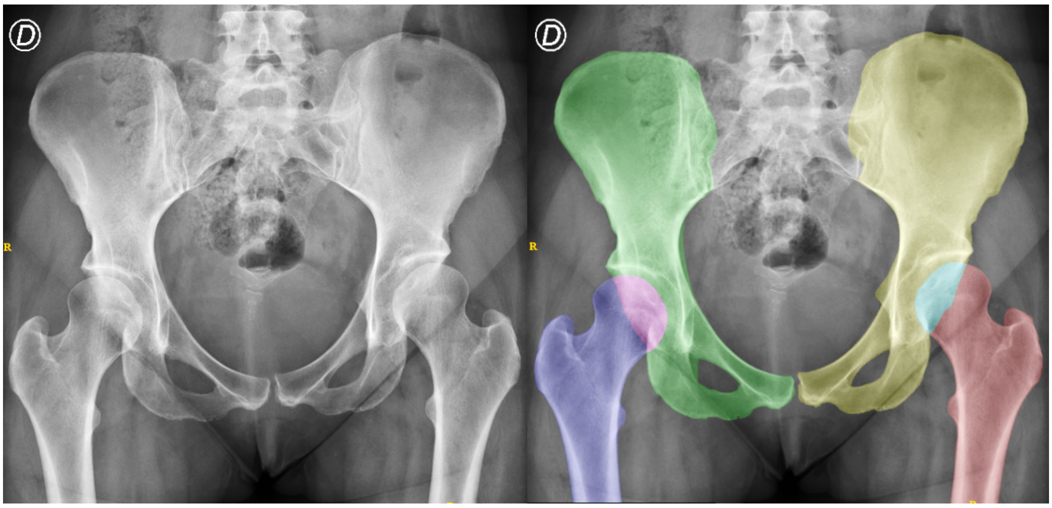

Figure 4. Pelvis CR Segmentation performed using ITK-SNAP software. (1A. Image without segmentation. 1B Image with the segmentation of 4 bones: right femur (blue), left femur (red), right pelvic bone (green) and left pelvic bone (yellow), and respective intersections

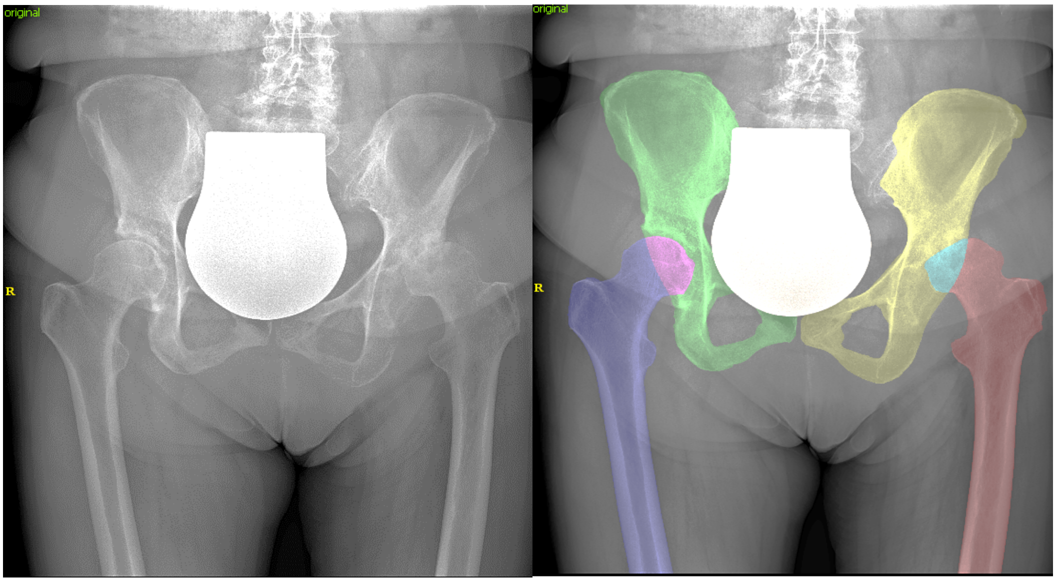

Figure 5. Pelvis CR Segmentation with a lead shield protector performed using the ITK-SNAP software (1A. Image without segmentation. 1B Image with the segmentation of 4 bones: right femur (blue), left femur (red), right pelvic bone (green) and left pelvic bone (yellow), and respective intersections

After several weeks, I was finally able to feel I had established a good level of proficiency with the software, setting a strong base for the subsequent phases of the internship where more advanced techniques and methods would be applied.

3.2. Middle stage

Following the internship planning, the next phase involved segmenting CT images. For that, I had to learn how to work with some new tools of the ITK-Snap software. To facilitate this transition, the data labeling team presented a new tutorial, providing the necessary foundation to proceed.

The initial attempt to use the region growing method was met with success. By following well-guided steps, with threshold values and parameters already established by the team, it was possible to segment all images within the CT scan across the three anatomical planes with acceptable precision. This method proved significantly more efficient and less labor -intensive compared to the extensive time previously required to segment a single image manually.

However, this technique is not without its drawbacks. Despite the initial efficiency, manual corrections across dozens, or even hundreds, of images were often necessary, leading to considerable time expenditure. Balancing the use of the region growing method with these manual corrections is crucial to minimize the total time required. This approach was frequently observed among specialists, who adeptly addressed the same challenges encountered.

While the region growing technique represents a significant advancement in segmenting CT images, it requires careful integration with manual corrections to achieve optimal efficiency and accuracy.

Over the course of the following weeks, multiple CT segmentations were performed for both knees and the pelvis. Demonstrative clips are presented in chronological order to illustrate the progression and improvement in segmentation skills. Initially, the segmentation process was time-consuming, especially when dealing with complex regions such as the pubic bone in the pelvis and the ischium. Over time, I was able to significantly reduce the time spent on each segmentation by applying anatomical knowledge and experience to overcome these challenges.

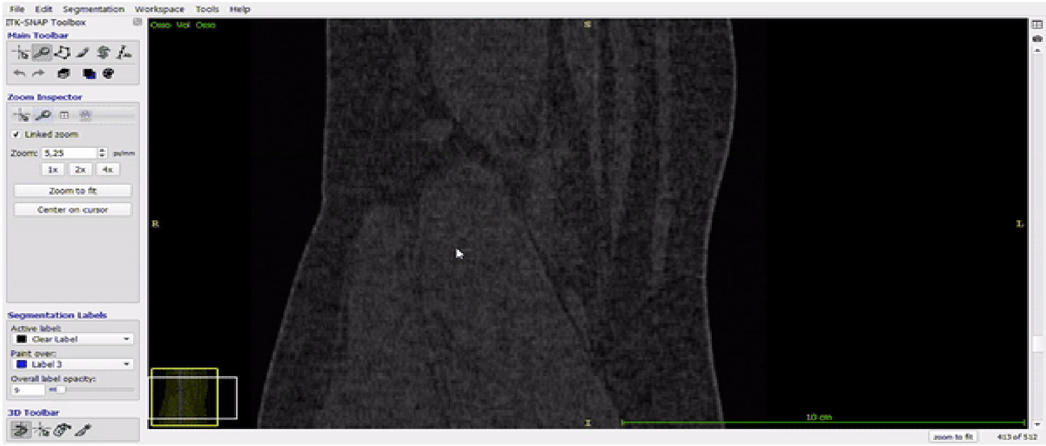

Figure 6. Knee CT Animated Segmentation (Coronal Plane) of 2 bones performed using the ITK-SNAP software – femur (blue) and tibia (yellow)

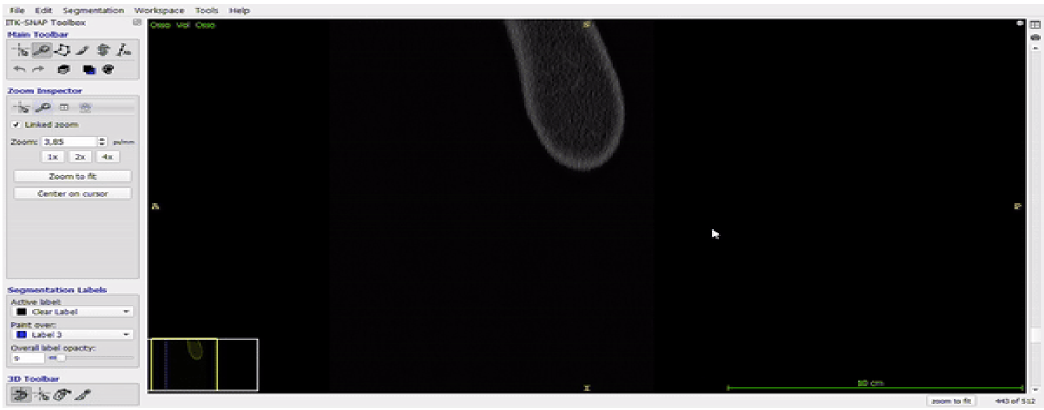

Figure 7. Knee CT Animated Segmentation (Sagittal Plane) of 3 bones performed using the ITK-SNAP software – femur (blue), patella (light purple) and tibia (yellow)

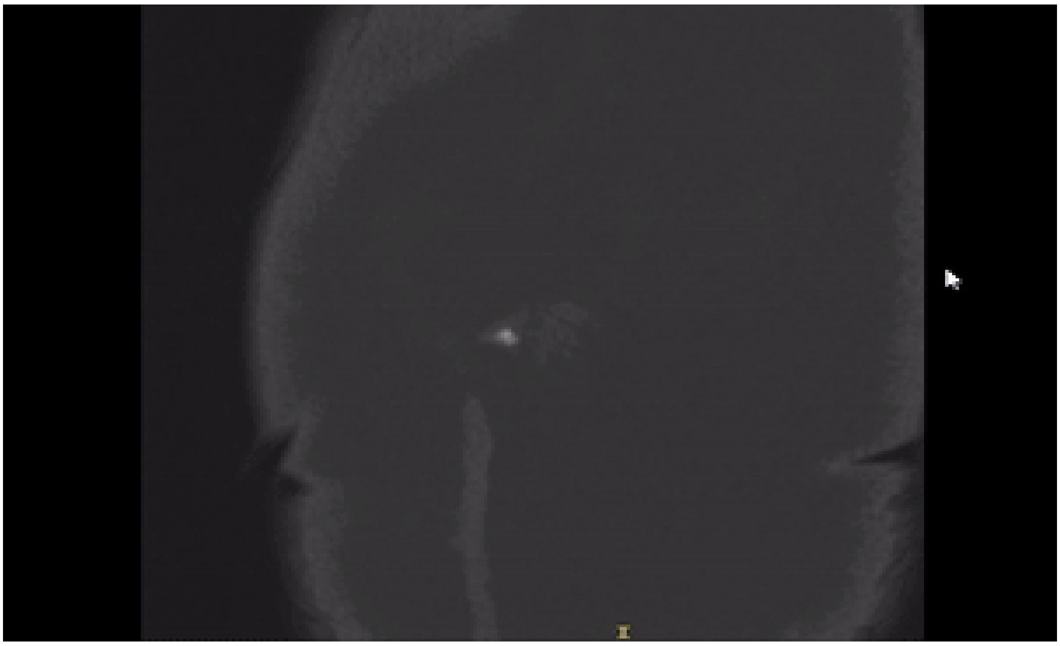

Figure 8. Pelvis CT Animated Segmentation (Coronal Plane) of 4 bones performed using the 3D-Slicer software - right femur (blue), left femur (red), right pelvic bone (green) and left pelvic bone (yellow)

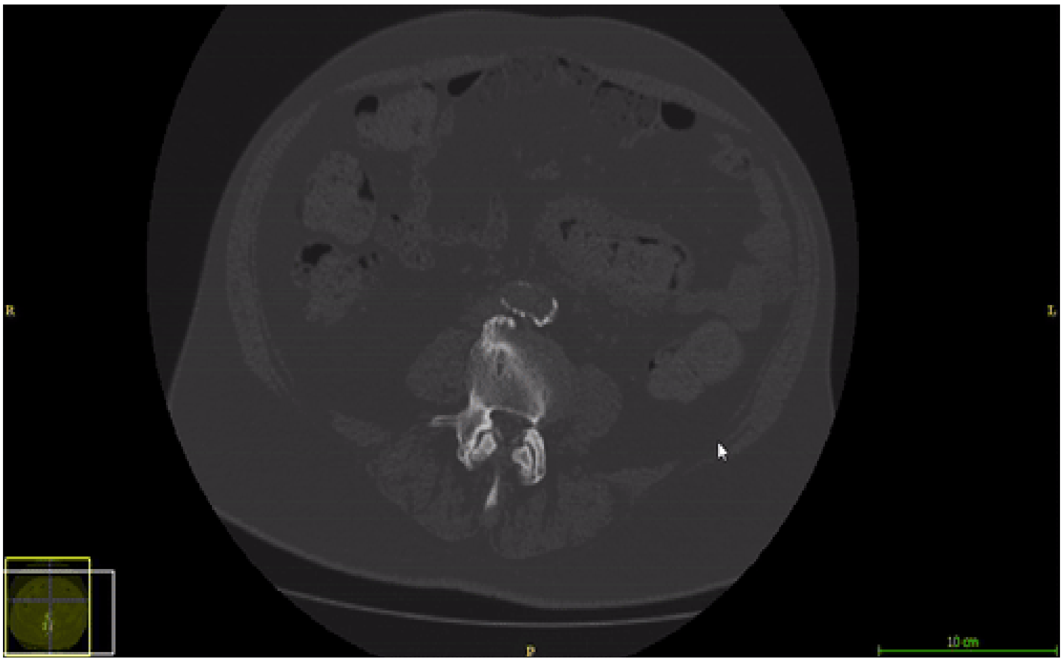

Figure 9. Pelvis CT Animated Segmentation (Transverse Plane) of the same 4 bones performed using the 3D-Slicer software - right femur (blue), left femur (red), right pelvic bone (green) and left pelvic bone (yellow)

After several weeks of practice, a satisfactory level of progress with the region growing method was achieved. This progress laid a solid foundation for the final phase of the internship, where multilevel threshold would be implemented in CT images in a new software, 3D-Slicer.

3.3. Final stage

The final stage of the internship introduced the use of 3D Slicer and multilevel thresholding, marking the most challenging adaptation period of all. Due to the modernity and increased complexity of 3D Slicer, there was a substantial amount to become acquainted with, and this had to be done all at once. Despite the software interface being very organized and user-friendly, resembling the structured layouts common in contemporary applications, discrepancies between image and software resolutions frequently resulted in poorly segmented areas.

This issue was addressed by gaining a deeper understanding of threshold selection, as the segmentation accuracy is closely tied to this critical step of the method. With the support of the image labeling team, it was identified that the problems stemmed from misapplication of the provided parameters and other software-specific idiosyncrasies. By mastering these nuances and refining the use of thresholds, these challenges were gradually overcome, leading to more precise segmentations and a more comprehensive grasp of the advanced capabilities of 3D Slicer, which provides the additional feature of creating a 3D-model of the performed segmentation, adding an additional rewarding aspect to the carried-out work.

The following figures display some of the 3D models and segmentations performed with resource to this software; despite existing a certain roughness associated with the bone's surface, it is also associated with segmentation/image imperfections.

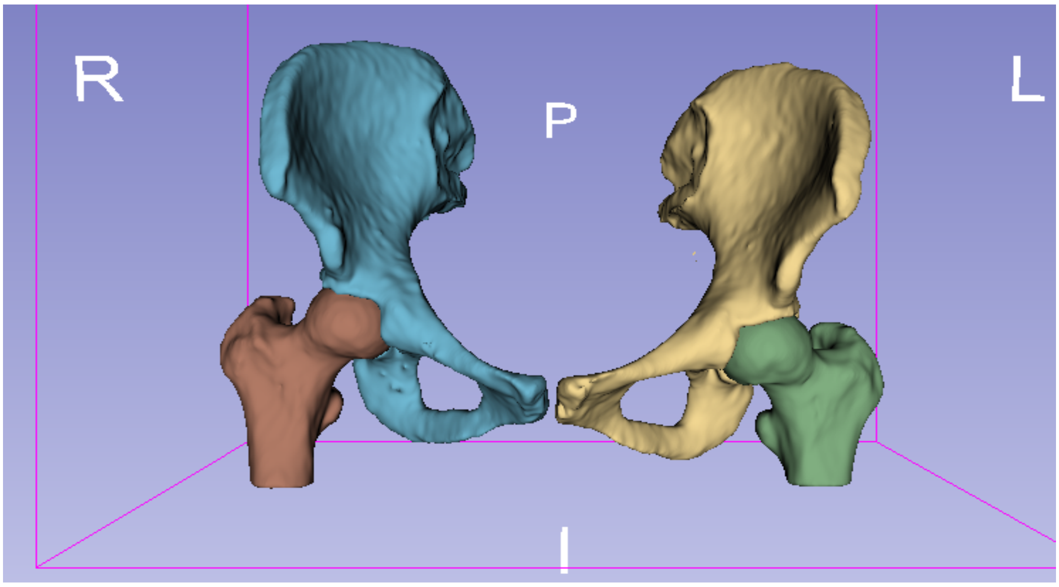

Figure 10. 3D model of the Pelvis generated from the segmentation of a CT image (Anterior view) using 3D-Slicer software

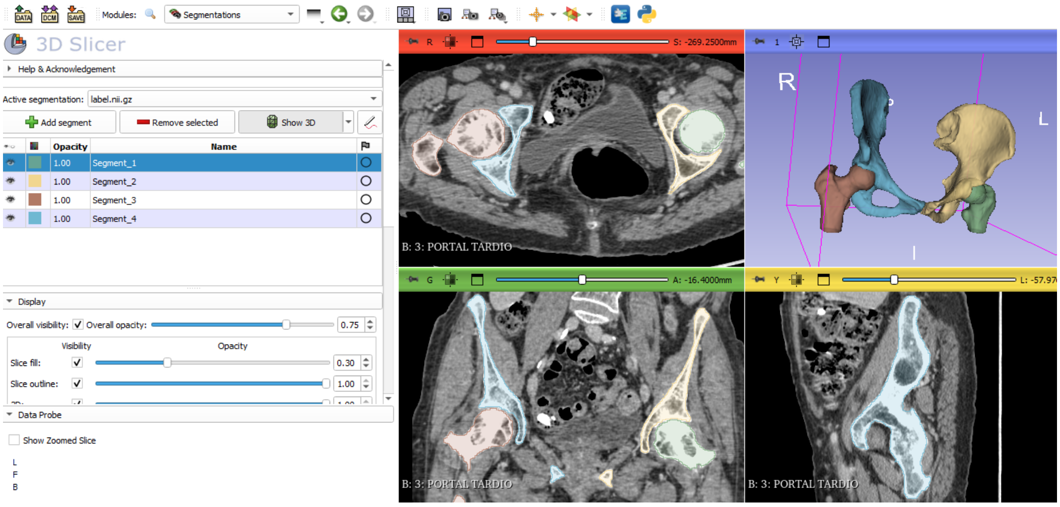

Figure 11. Overall interface view of Pelvis CT Segmentation using 3D-Slicer software

4. Significance and Broader impacts

This chapter will be dedicated to reflecting and analyzing the impact of this internship on both the student's academic journey and its alignment with the Sustainable Development Goals (SDGs).

The Sustainable Development Goals (SDGs), adopted by all United Nations Member States in 2015, provide a shared blueprint for peace and prosperity for people and the planet, now and into the future. They consist of 17 interconnected goals that address global challenges, including poverty, inequality, climate change, environmental degradation, peace and justice. The SDGs aim to create a better and more sustainable world by 2030.

4.1. Importance in the academic formation

The entire internship experience has been profoundly influential in shaping my academic formation, offering valuable insights that have contributed significantly to my development, as I intend to keep carrying them throughout my working life. Working in a real-world environment has underscored the importance of several key aspects of professional life, further described.

One of the most demanding aspects of the internship was managing strict deadlines, which contributed significantly to my experience through developed practices and habituation. This skill is a crucial one in the professional realm, as it translates directly to the everyday working rhythm.

Another significant challenge encountered was the monotony of most job tasks, since repetitive duties can often lead to a sense of disillusionment and lack of fulfillment. This has been a critical learning point, emphasizing the importance of passion and genuine interest in one’s chosen field. The experience has reinforced that to excel and find satisfaction in a career, one must pursue work that is intrinsically motivating. In the biomedical field, this translates to a dedication to continuous learning and a commitment to contributing to advancements in health and medicine.

Nevertheless, the sporadic but profound sense of being part of something greater, coupled with the satisfaction of a job well done, from time to time provided some sense of fulfillment. These moments of realization, where the impact of the work becomes clear, can be very motivating: they remind us of the broader purpose of our efforts and the difference we can make in this field. This experience has instilled in me a deeper appreciation for the tangible outcomes of hard work and dedication.

Despite the challenges, the internship also highlighted the importance of a supportive and collaborative work environment. The mutual help among co-workers created a pleasant and productive atmosphere and this sense of community and teamwork is crucial in any professional setting, but it can also be particularly significant in the biomedical field, where collaborative research and shared knowledge drive innovation and success. The ability to work well with others, share insights, and provide support has proven to be one of the most rewarding aspects of the internship, fostering a sense of belonging and mutual respect.

Throughout the internship, I have acquired numerous tools and skills that are directly applicable to my academic and future professional endeavors in the biomedical field. Practical skills such as data analysis and the use of specialized software for segmentation have been invaluable, and these can always prove useful in biomedical engineering. Additionally, soft skills like problem-solving, effective communication, and adaptability have been honed. These tools are essential for any biomedical professional, enabling them to conduct research, produce results and communicate findings effectively.

In conclusion, the internship has been a pivotal component of my academic formation, providing both challenges and invaluable learning opportunities. The experiences gained have not only enhanced my practical skills but also reinforced the importance of pursuing work that is both fulfilling and impactful. The lessons learned about time management, teamwork and finding genuine interest in one's work are indispensable as I continue my journey in the biomedical field, committed to making meaningful contributions to science and health.

4.2. SDGs (Sustainable Development Goals)

SDS	Target	Contribution
3	4	Accurate segmentation of bone structures aids in diagnosing and treating musculoskeletal disorders, which fall under non-communicable diseases. This contributes to reducing premature mortality associated with conditions like osteoporosis, fractures, and other skeletal disorders.
8	4	Adoption of AI-driven segmentation reduces resource consumption and waste in medical imaging, promoting efficient production practices.
9	4	AI-driven medical image segmentation enhances healthcare efficiency by accurately guiding implant placements, reducing wastage of materials and promoting clean technology adoption. This supports sustainable healthcare infrastructure development worldwide.
	5	The internship's focus on advanced segmentation contributes to technological advancements in healthcare technology, fostering innovation and increasing research and development efforts in medical imaging.
10	2	AI-driven medical imaging helps provide more accurate diagnoses and personalized treatment plans, thereby preventing people with medical conditions from living suboptimal lives.
	3	AI technologies in healthcare contribute to reducing disparities in health outcomes by providing more equitable access to advanced medical diagnostics and treatments, regardless of socio-economic status or geographic location.
12	2	AI technologies in medical imaging contribute to more efficient use of healthcare resources by improving diagnostic accuracy and reducing the need for unnecessary procedures and tests, thus conserving medical resources.
	4	AI applications in medical imaging help in minimizing environmental impacts by reducing the need for repeat imaging studies and optimizing healthcare processes, thereby lowering overall resource consumption and waste generation in healthcare facilities.
	5	Optimizing AI based segmentation can substantially decrease the amount of generated waste

5. Conclusion

The internship experience in medical image segmentation has been a transformative journey, shaping both my academic formation and understanding of sustainable development goals. Through hands-on work with various segmentation techniques and software tools, I have gained practical skills, theoretical knowledge, and invaluable insights into the complexities of biomedical imaging.

The evolution from manual segmentation to advanced techniques like region growing and multilevel thresholding mirrors the ongoing advancements in the field of image segmentation, reflecting a commitment to improving both the accuracy and efficiency of medical image analysis. These methods collectively contribute to the development of robust models capable of automating the segmentation process, thus enhancing diagnostic capabilities and clinical outcomes.

Beyond the technical skills acquired, the internship experience has highlighted a myriad of key aspects inherent to the professional life. By working closely with professionals, it also served as a gate into the relationships one establishes in the working environment.

Furthermore, the alignment of the internship work with the Sustainable Development Goals (SDGs) underscores its broader impact on global efforts toward sustainable development. From promoting good health and well-being to fostering economic growth and reducing inequalities, the work in medical image segmentation contributes to multiple dimensions of sustainable development, emphasizing the interconnectedness of social, economic and environmental challenges.

In summary, the internship has become a key component of my academic journey, providing both challenges and invaluable learning opportunities. As I continue my journey in the biomedical field, committed to making meaningful contributions to science and health, I carry with me the lessons learned and experiences gained during this transformative period. I am grateful for the guidance, support and mentorship received throughout this journey, and I look forward to applying these skills and insights in future endeavors, hopefully contributing to a better world.

6. References

1. Ana Maria Mendonça, “Image Segmentation”, 2024

2. 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.

3. Yepes-Calderon, F., & McComb, J. G. (2023). Eliminating the need for manual segmentation to determine size and volume from MRI. A proof of concept on segmenting the lateral ventricles. *PLoS ONE*, *18*(5 May). https://doi.org/10.1371/journal.pone.0285414

4. Niu, Z., & Li, H. (2019). Research and analysis of threshold segmentation algorithms in image processing. *Journal of Physics: Conference Series*, *1237*(2). https://doi.org/10.1088/1742-6596/1237/2/022122

5. PunamThakare,. (2011). A Study of Image Segmentation and Edge Detection Techniques. International Journal on Computer Science and Engineering. 3.

6. Houssein, E. H., Mohamed, G. M., Ibrahim, I. A., & Wazery, Y. M. (2023). An efficient multilevel image thresholding method based on improved heap-based optimizer. *Scientific Reports*, *13*(1). https://doi.org/10.1038/s41598-023-36066-8

7. ITK-SNAP. (n.d.). *ITK-SNAP: An interactive software tool for segmentation of 3D medical images*. Retrieved June 18, 2024, from http://www.itksnap.org

8. 3D Slicer. (n.d.). *3D Slicer: A free open-source software package for visualization and image analysis*. Retrieved June 18, 2024, from http://www.slicer.org