DESIGN AND IMPLEMENTATION OF A DEEP LEARNING MODEL FOR PULMONARY ARTERIAL SEGMENTATION IN COMPUTED TOMOGRAPHY (CT) IMAGES

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RESUMEN

TÍTULO: DISEÑO E IMPLEMENTACIÓN DE UN MODELO DE APRENDIZAJE PROFUNDO PARA LA SEGMENTACIÓN DE ARTERIAS PULMONARES EN IMÁGENES DE TOMOGRAFÍA COMPUTARIZADA *

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PALABRAS CLAVE: ARTERIAS PULMONARES, SEGMENTACIÓN, TOMOGRAFÍA COMPUTARIZADA (TC), APRENDIZAJE PROFUNDO.

DESCRIPCIÓN:
La Embolia Pulmonar (EP) es una condición potencialmente mortal en la que un coágulo sanguíneo bloquea una arteria en los pulmones. Permanece como una de las condiciones más desafiantes para diagnosticar y tratar en el departamento de emergencias. Como tipo de enfermedad cardiovascular, la EP contribuye a la principal causa de muerte a nivel mundial, según la Organización Mundial de la Salud. La detección temprana y el tratamiento oportuno son críticos para mejorar los resultados del paciente. En este proyecto, buscamos desarrollar e implementar un algoritmo para la segmentación automatizada de arterias pulmonares como un paso crucial hacia la identificación de EP. Tuvimos acceso a una base de datos de 130 volúmenes 3D con etiquetado refinado de las arterias pulmonares. La combinación de herramientas de alto desempeño y tecnología avanzada tiene un gran potencial para la detección y tratamiento temprano de enfermedades pulmonares, especialmente en entornos con recursos limitados. Específicamente, proponemos la implementación de una arquitectura llamada ResD-Unet, basada en la red Unet, complementada con bloques residuales y capas de convolución interconectadas. Los resultados obtenidos son moderados, pero constituyen un paso inicial para la solución del problema.

* Trabajo de grado

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ABSTRACT

TITLE: DESIGN AND IMPLEMENTATION OF A DEEP LEARNING MODEL FOR PULMONARY ARTERIAL SEGMENTATION IN COMPUTED TOMOGRAPHY (CT) IMAGES *

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KEYWORDS: PULMONARY ARTERIAL, SEGMENTATION, COMPUTED TOMOGRAPHY(CT), DEEP LEARNING.

DESCRIPTION:

Pulmonary Embolism (PE) is a life-threatening condition in which a blood clot blocks an artery in the lungs. It remains one of the most challenging conditions to diagnose and treat in the emergency department. As a type of cardiovascular disease, PE contributes to the leading cause of death worldwide, according to the World Health Organization. Early detection and timely treatment are critical to improving patient outcomes. In this project, we sought to develop and implement an algorithm for automated pulmonary artery segmentation as a crucial step toward PE identification. We had access to a database of 130 3D volumes with refined labeling of pulmonary arteries. The combination of high-performance tools and advanced technology has great potential for early detection and treatment of lung diseases, especially in resource-limited settings. Specifically, we propose the implementation of an architecture called ResD-Unet, based on the Unet network, complemented with residual blocks and interconnected convolution layers. The results obtained are modest, but constitute an initial step towards solving the problem.

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* Bachelor Thesis

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INTRODUCTION

Pulmonary embolism (PE) occurs when a clot (thrombus) that formed somewhere in the body dislodges, travels through the right side of the heart to the lungs and blocks one of the arteries that supplies blood flow to the lungs. Pulmonary embolism remains one of the most challenging medical diseases in the emergency department.[1] As reported by the World Health Organization, cardiovascular diseases (CVDs) are the leading cause of death globally, taking an estimated 17.9 million lives each year. CVDs are a group of disorders of the heart and blood vessels that include coronary heart disease, cerebrovascular disease, rheumatic heart disease and other conditions. PE is a potentially life-threatening diagnosis that is seen in patients with chest pain and/or dyspnea, but can span the clinical spectrum of medical presentations. [2] According to the European Society of Cardiology, pulmonary embolism is the third most common cause of acute cardiovascular death after myocardial infarction and stroke. A high mortality rate persists despite advances made in treatment.

In Colombia, cardiovascular disease accounts for nearly 30% of total deaths and a

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[1] APRN NNP-BC; Amanda Holmes MSN APRN NNP-BC Evaline Sims MSN APRN AGACNP-BC CCRN; Sandra K. Hanneman PhD RN FAAN Jamie L. Gilley MSN. *Pulmonary embolism: Surveillance is key*. Vol. 17. 3. Washington, DC, USA: American Nurse Journal, 2013.

[2] David W. Ouellette and Catherine Patocka. "Pulmonary Embolism". In: *Emergency Medicine Clinics of North America* 30.2 (2012). Thoracic Emergencies, pp. 329–375. DOI: https://doi.org/10.1016/j.emc.2011.12.004.

diagnosis of PE was obtained every 3.2 days. [3] [4] The overall hospital mortality due to PE in Colombia is approximately 14.8%. Proper management may reduce this rate from 15-30% down to 3-10%. [5] [6] Although almost 20% of patients who are treated for pulmonary embolism die within 90 days. [7] The morphological assessment of the Pulmonary Artery (PA) is essential to evaluate several Pulmonary Vascular Diseases (PVD). Most patients with Pulmonary Hypertension, present a remodeled main PA with a diameter considerably larger than that of a control subject and thus, being an important biomarker for predicting and detecting hypertension [8]. Hypertension is a disease that affects the arteries of the lungs and the right side of the heart, in which the blood vessels of the lungs are narrowed, blocked or destroyed in such a way that

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[3] D E Rebellon-Sanchez et al. "Correlates between cardiovascular mortality and social determinants in Colombia, 2008 to 2017". In: *European Heart Journal* 42.Supplement$_1$ (Oct. 2021). ehab724.3142. DOI: 10.1093/eurheartj/ehab724.3142. eprint: https://academic.oup.com/eurheartj/article-pdf/42/Supplement_1/ehab724.3142/41051818/ehab724.3142.pdf.

[4] Pablo Ramón Gil Torres et al. "Pulmonary Embolism Registry of a South American Hospital". In: *European Respiratory Journal* 54.suppl 63 (2019). DOI: 10.1183/13993003.congress-2019.PA1458. eprint: https://erj.ersjournals.com/content.

[5] Rodolfo José Dennis Verano et al. "Curso clínico y supervivencia en embolia pulmonar: Resultados del registro multicéntrico colombiano (EMEPCO)". in: *Acta Médica Colombiana* 33.3 (2008), pp. 111–116.

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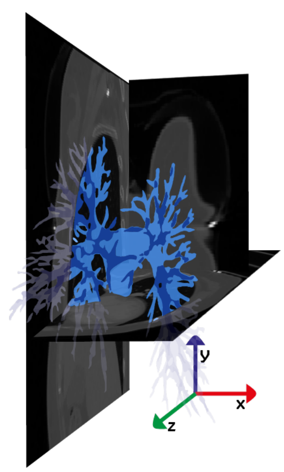
[8] Karen López-Linares Román et al. "3D Pulmonary Artery Segmentation from CTA Scans Using Deep Learning with Realistic Data Augmentation". In: *Image Analysis for Moving Organ, Breast, and Thoracic Images*. Ed. by Danail Stoyanov et al. Cham: Springer International Publishing, 2018, pp. 225–237.

the heart must make a greater effort to pump blood[9]. Computed tomography (CT) plays an important role in the diagnosis of the diseases named above, as it allows visualizing and evaluating the pulmonary anomaly and to devise a minimally invasive surgical procedure to operate or create treatments prolonging the patient's quality of life. The goal of this project is to develop and implement an algorithm for automated segmentation of pulmonary arteries in dorsal CT images. Due to the complexity of the topology in pulmonary arteries, as shown in the Figure 1, traditional medical image segmentation methods have a limit to solving these problems. As the popularity, significant advances, and reliable results of neural networks have fostered their adoption for solving more complex problems in medical imaging, we sought to develop and implement an algorithm for automated segmentation of pulmonary arteries as a step toward the future development of a method to assess pulmonary vascular pathophysiology.

Figure 1. Segmentation of pulmonary arteries with CT views as background.
Axis x: axial; axis y: coronal and axis z: saggital



[9] P. Nardelli et al. "Deep-learning strategy for pulmonary artery-vein classification of non-contrast CT images". In: *2017 IEEE 14th International Symposium on Biomedical Imaging (ISBI 2017)*. 2017, pp. 384–387. DOI: 10.1109/ISBI.2017.7950543.

1. OBJECTIVES

1.1. General objective

- To develop and implement an algorithm for automated segmentation of pulmonary arteries in dorsal CT images.

1.2. Specific objectives

1. To design a preprocessing strategy for each of the views of the Computed Tomography: axial, sagittal and coronal, for further processing with a neural network.
2. To modify the U-NET architecture for its utilization in the segmentation of pulmonary arteries in CT images.
3. To train the proposed architecture in a CT dataset.
4. To evaluate the performance of the proposed architecture by Multi-level Dice's Similarity Coefficient.

2. PREVIOUS WORK

In the literature, we found little background on the segmentation of pulmonary arteries in CT images. Among the most important, we have the hybrid method, which combines image processing techniques with region growing, and handles topological changes in contours and achieve sub-pixel accuracy to detect blood vessel boundaries with a new stopping criterion was shown to be more effective[10]; a Geodesic Active Contour model[11] that is based on replacing the traditional velocity constant, which is constructed by the information provided by the grayscale of area. Experimental results show that this algorithm can achieve automatic segmentation of the pulmonary artery and has a high matching rate with the physician's segmentation results. Deep learning architectures based on Convolutional Neural Networks have also been considered as an integrated solution for airway and arterial vein segmentation, and its components can be used to design solutions for other tasks[12]. The use of deep networks has shown significant advances and reliable results in many computer vision tasks, including image segmentation, target recognition, motion tracking and image classification.

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[10] Yousef Ebrahimdoost et al. "Automatic segmentation of Pulmonary Artery (PA) in 3D pulmonary CTA images". In: *2011 17th International Conference on Digital Signal Processing (DSP)*. 2011, pp. 1–5. DOI: 10.1109/ICDSP.2011.6004964.

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[12] Yulei Qin et al. "Learning Tubule-Sensitive CNNs for Pulmonary Airway and Artery-Vein Segmentation in CT". in: *IEEE Transactions on Medical Imaging* 40.6 (2021), pp. 1603–1617. DOI: 10.1109/TMI.2021.3062280.

The most commonly implemented architectures in pulmonary artery segmentation are DenseUnet[13], CE-Net[14], UNet++[15] and ResD-Unet[16]. Based on our literature review, the ResD-Unet architecture shows a good performance in DSC, Recall, Precision, and SSIM, thus verifying the effectiveness of the proposed framework; therefore, our research is based on the use and modification of this network.

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[13] Aakash Kaku et al. "DARTS: DenseUnet-based Automatic Rapid Tool for brain Segmentation". In: (Nov. 2019).

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3. MATERIALS AND METHODS

3.1. Dataset

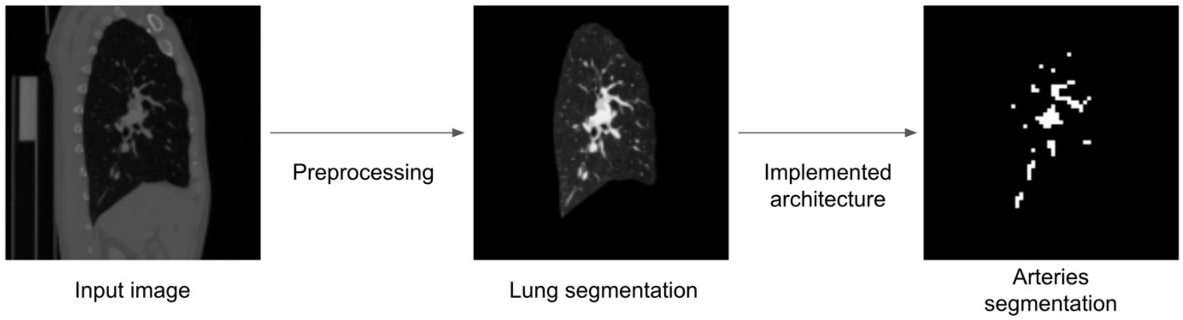
We have access to a database of 130 3D volumes with refined labeling of the pulmonary arteries [17]. The data are contrast-enhanced CT pulmonary angiographies (CTPA) which are obtained from a dual-source 64-slice CT scanner at Harbin Medical University, Harbin, China. Ten experts with more than 5 years of clinical experience participated in the labeling work. The annotation is performed on the basis of region growing algorithm using MIMICS software [16]. The construction of our deep learning model will be performed with the following data distribution: 80 for the training dataset (62%), 20 for the closed test dataset (15%) and 30 for the validation dataset (23%). Finally, the Dice Similarity Coefficient (DSC) will be used to evaluate the model results.

3.2. Implemented algorithm

The process was divided into two stages, the first stage consists of the segmentation of the lung and the second stage consists of the use of a network for the identification of the arteries within the previously segmented region as shown in the Figure 2.
For computational cost reasons it was decided to make a sub-database of the sagittal view, taking images between slices 70 to 230 and 300 to 440, which contain information of the right and left lung respectively. In this way, a total of 12.000 images were obtained.

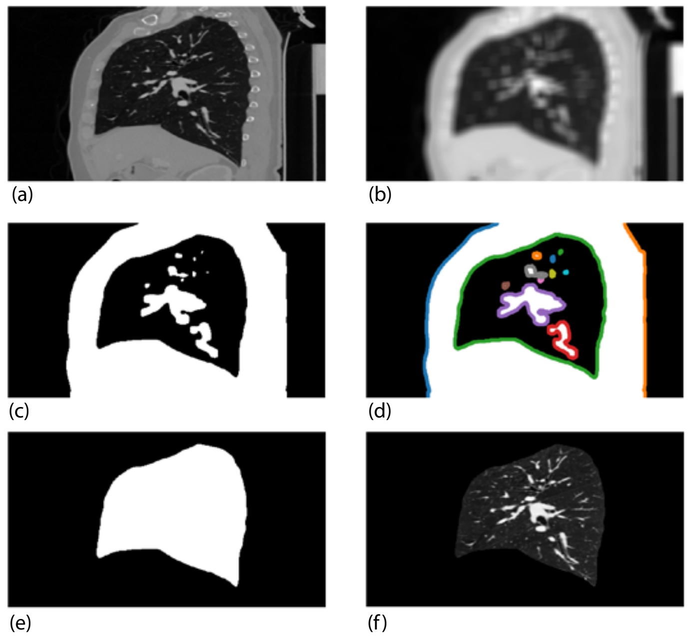
[17] Kuanquan Wang et al. *Pulmonary Artery Segmentation Challenge 2022*. Mar. 2022. DOI: 10.5281/zenodo.6361906.

Figure 2. Image segmentation processing with the implemented algorithm.



3.2.1. Lung Segmentation For the lung segmentation, we used classical techniques: the Gaussian filter was applied to the input image with a 15x15 kernel, then the image was thresholded by Hounsfield units between -600 and -400. After that, the marching square's algorithm was used to detect the edges. Having the edges, it was searched which edge or edges were a closed figure using the formula of the shortest distance between two points, defining that it was going to be closed when the distance between the initial point and the final point was less than 10 pixels. Apart from the closed figure condition, the contour had to have an area greater than 1900 square pixels. In case of detecting more than one contour, the two largest contours would be taken as maximum. Finally, the contours selected by the algorithm are taken to create the binary mask as shown in Figure 3.

Figure 3. Preprocessing for lung segmentation. (a) Original image; (b) Image processed with the Gaussian filter; (c) Segmented image using Hounsfield units; (d) Contour detected through Marching Square; (e) Mask obtained through morphological operations; (f) Original image with mask



3.2.2. Artery segmentation For the artery segmentation we are based on an original Unet network but with some modifications, such as a Residual Block and in each block includes a batch normalization layer, a rectified linear unit activation (ReLU) layer and two convolution layers with the stride of 2 and 1, which is the basis of the ResD-Unet. The use of an Encoder-block and Decoder-block can improve the performance can be consistent[18], each block is formed with the similar layers than the Residual block as shown in Figure 4.

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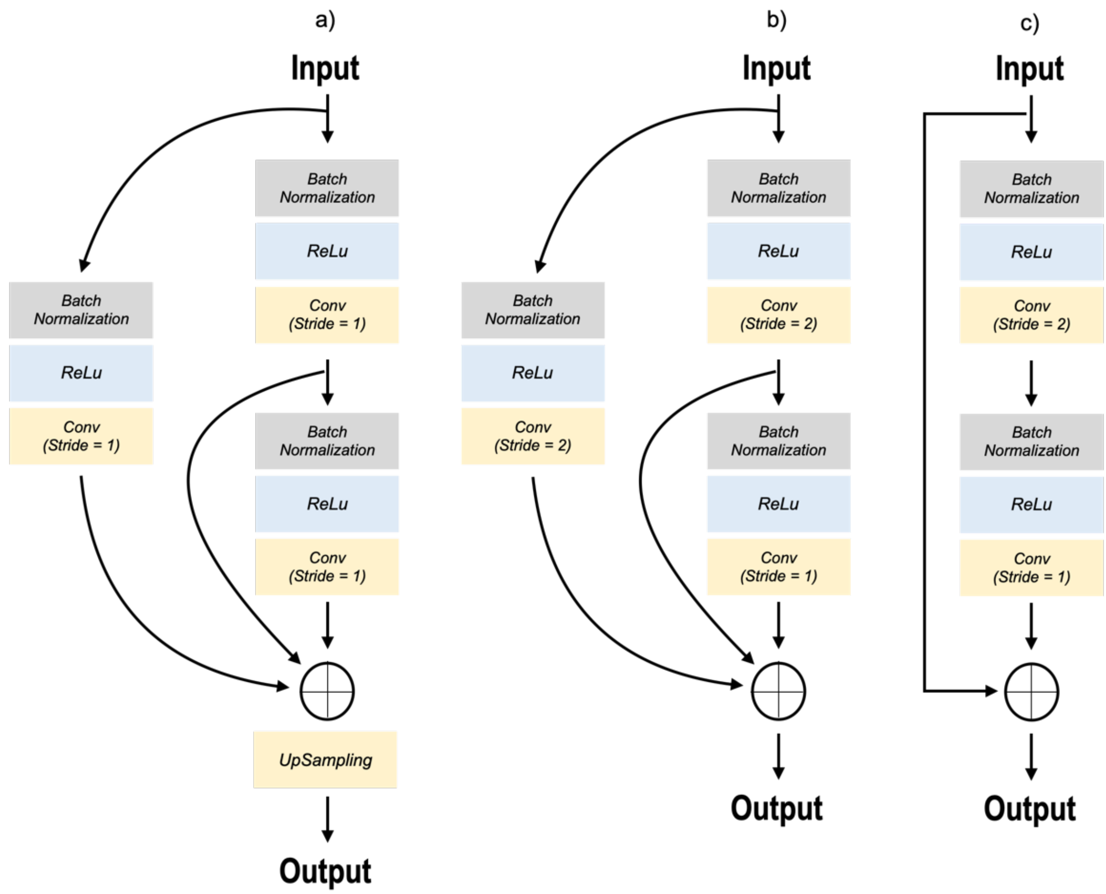
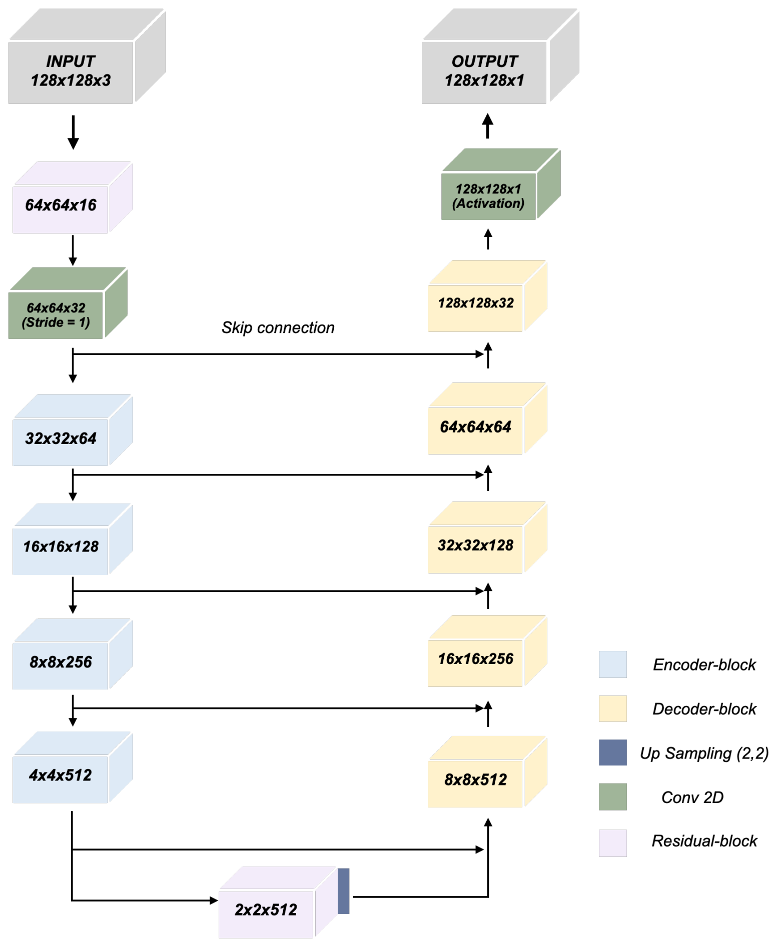
[18] Jost Tobias Springenberg et al. *Striving for Simplicity: The All Convolutional Net*. DOI: https://doi.org/10.48550/arXiv.1412.6806.

Figure 4. Residual-dense blocks. **a)** Decoder block **b)** Encoder block **c)** Residual block



In this architecture, we use the ADAM optimizer. Images with an input size of 128×128×3 pass through a residual block, four encoders, and five decoders. A decoder was added, which allows one more level of comparison with the skip connection, as shown in the Figure 5. The Early Stopping was used to avoid overfitting.

Figure 5. Implemented Architecture



3.3. Performance Measure

For the performance of the arteries segmentation, we use the Dice Similarity Coefficient (DSC). The DSC is a simple and useful summary measure of spatial overlap, which can be applied to studies of reproducibility and accuracy in image segmentation [19]. The value of a DSC ranges from 0, indicating no spatial overlap between

[19] Bharatha A-Tempany CM Kaus MR Haker SJ-Wells WM 3rd Jolesz FA Kikinis R Zou KH Warfield SK. "Statistical validation of image segmentation quality based on a spatial overlap index." In: *Academic radiology* 11 (2004), pp. 178–189. DOI: https://doi.org/10.1016/s1076-6332(03)00671-8.

two sets of binary segmentation results, to 1, indicating complete overlap and is calculated with the equation 1 [20].

$$DSC(x, y) = \frac{2|x \cap y|}{|x| + |y|} \tag{1}$$

Where *x* is the predicted set of pixels and *y* is the real image.

3.4. Implementation Details

For this project, we used Google Colaboratory, which is a cloud service, based on Jupyter Notebooks. The use of Colab Pro GPUs and TPUs. Each TPU packs up to 180 Teraflops of floating-point performance and 64 GB of high-bandwidth memory onto a single board, and the GPU is an NVIDIA K80 accelerator. A computer with a ninth-generation Intel 7 processor, NVIDIA GeForce RTX 20-series graphics card and up to 6 GB GDDR5 dedicated memory and libraries such as: Scikit-learn, PyTorch, TensorFlow, Keras and OpenCV.

[20] Lee R. Dice. “Measures of the Amount of Ecologic Association Between Species”. In: *Ecology* 26.3 (1945), pp. 297–302. DOI: https://doi.org/10.2307/1932409.

4. EXPERIMENTS AND RESULTS

4.1. Lung Segmentation Results

A manual segmentation was performed to obtain the smallest possible margin of error, and was used as a method of evaluating the results for the lung segmentation algorithm developed, whose objective is to introduce only the lung region and not the entire CT image into the final network. For this purpose, a set of 1200 images corresponding to 10 patients was randomly selected, and a manual segmentation was performed using the 3D Slicer tool, which consisted mainly of selecting the region of interest, the lungs. The segmentation process is based on the selection of a Threshold range between -800 and -400, which was used to perform the level tracing, then a Grow from seeds method was applied to cover the entire lung area and finally a smoothing was applied with a kernel size of 10x10, this mask was saved in Nifti format per patient. With this technique, the result was 86% similarity using DSC.

4.2. Artery segmentation results

This network was trained with 12.000 images. After 30 training epochs, the prediction of the test images was performed. The results of comparing the label/mask images with the predictions using the Dice coefficient are presented below in Figure 6. These results are summarized in Table 1

Table 1. Metrics Dice Coefficient

Metrics	Result
Mean	0.61412
Median	**0.63681**
Maximum	0.94901

Figure 6. Histogram Dice Coefficient

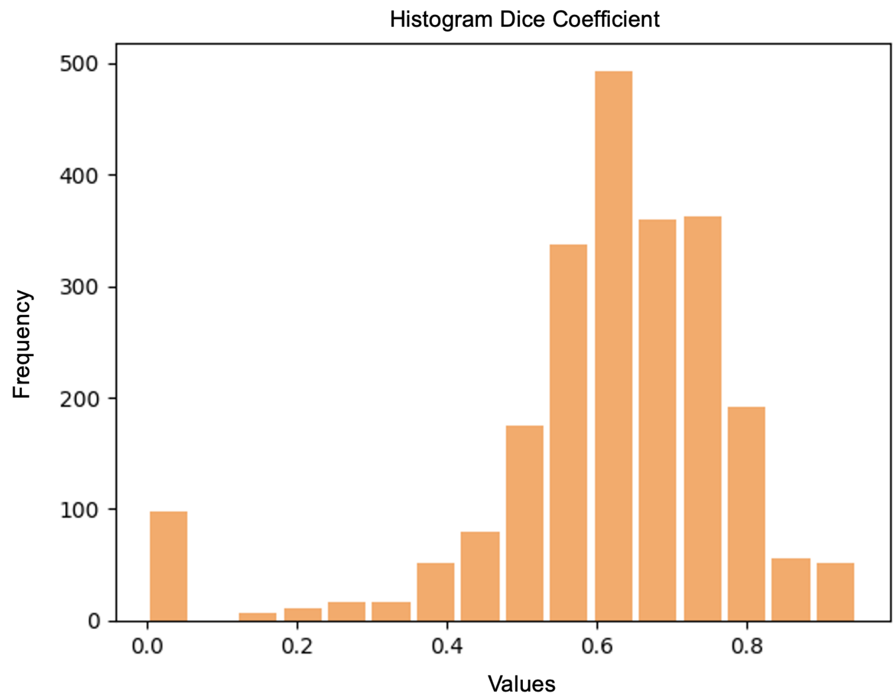
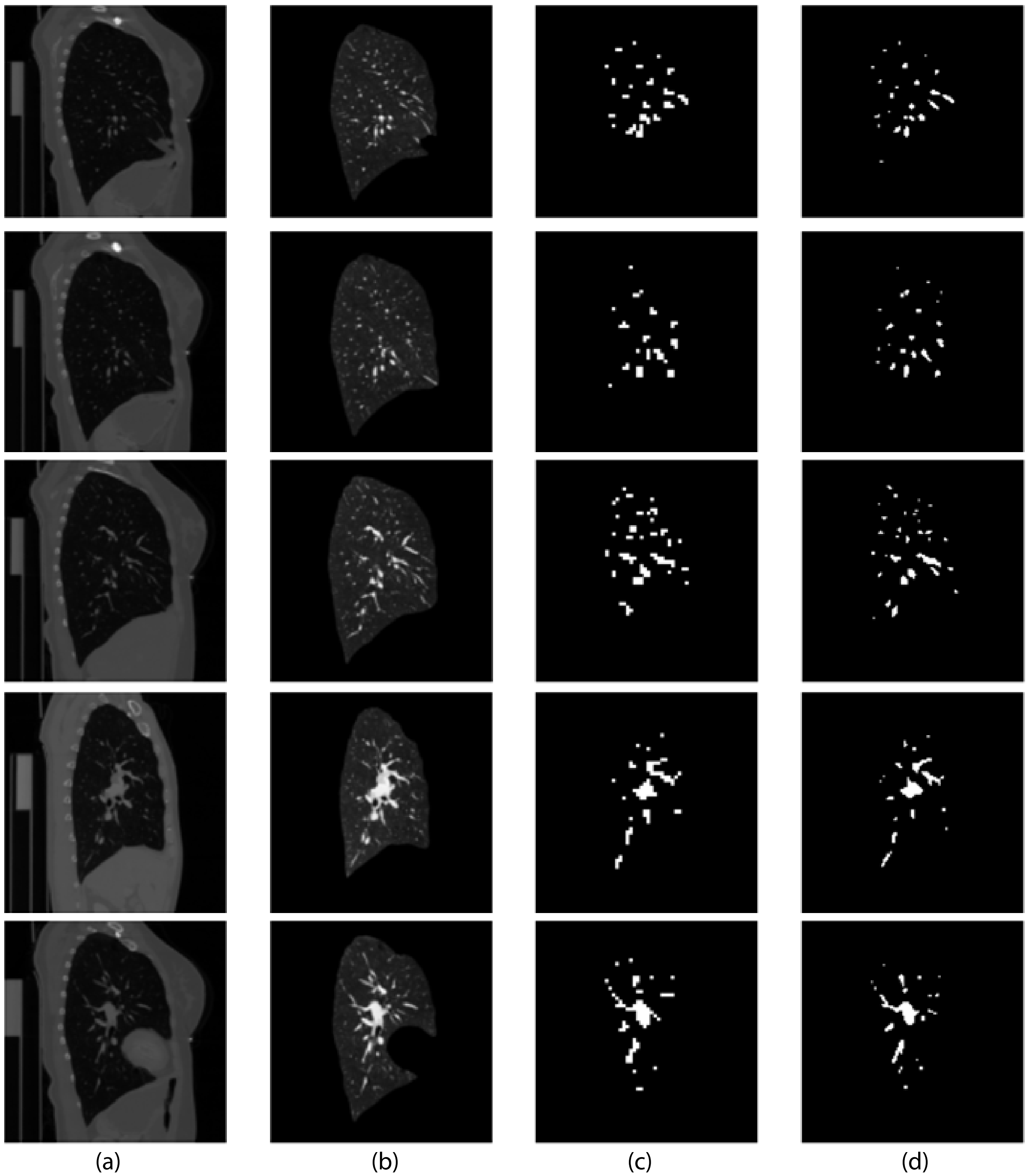


Figure 7 shows an example of how the network works on a given set of images. The code used can be found in the repository of the project.

Figure 7. Segmentation examples. a) CT image; b) Segmented and preprocessed image; c) Segmented image by algorithm; d) Ground-truth



5. CONCLUSIONS

In this project, we developed an algorithm for the segmentation of pulmonary arteries in CT images. The algorithm is based on a processing stage that identifies the lung, a neural network based on the ResD-Unet architecture, composed of a conventional Unet interconnected with layers of residual blocks and convolution blocks. The performance of the neural network was 63% using as measured by Dice Similarity Coefficient (DSC) index on a database of 30 3D volumes with refined labeling of the pulmonary arteries. These results are modest, but serve as a starting point for improving pulmonary artery segmentation.

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