

Automated Lung Region Segmentation in Pediatric Chest Radiography

Segmentação Automática da Região Pulmonar em Radiografias Pediátricas de Tórax

Afonso Ueslei da Fonseca^{1*}, Juliana Paula Felix¹, Gabriel da Silva Vieira², Deborah Fernandes¹, Fabrizzio Soares¹

Abstract: In chest radiographs, the automatic identification of regions, structures, or objects that compose it can help the professional in the area to perform their reading and analysis more assertively, promoting the improvement and efficiency of the diagnosis. In the present work, we propose a method to segment the lung fields in pediatric chest radiographs (PCXR). Based on digital image processing operations and rules, the proposal is evaluated on a PCXR images dataset. The results are satisfactory for the different classes of images analyzed, indicating that the proposed method can be helpful in the preprocessing stages of more complex flows.

Keywords: Lung Segmentation — Chest Radiograph — Rules — Image Processing

Resumo: Nas radiografias de tórax, a identificação automática de regiões, estruturas ou objetos que a compõem pode auxiliar o profissional da área a realizar sua leitura e análise de forma mais assertiva, promovendo a melhoria e eficiência do diagnóstico. No presente trabalho, propomos um método para segmentar os campos pulmonares em radiografias pediátricas de tórax (RXPT). Com base em operações de processamento digital de imagens e uso de regras, a proposta é avaliada em um banco de dados de imagens RXPT. Os resultados satisfatórios para diferentes classes de imagens analisadas indicam que o método proposto pode ser útil em etapas de pré-processamento de fluxos mais complexos.

Palavras-Chave: Segmentação Pulmonar — Radiografia de Tórax — Regras — Processamento de Imagem

¹Instituto de Informática, Universidade Federal de Goiás, Goiânia - GO, Brazil

²Instituto Federal Goiano, Campus Urutaí, Urutaí - GO, Brazil

*Corresponding author: afonsoueslei@ufg.br

DOI: <http://dx.doi.org/10.22456/2175-2745.130579> • Received: 03/03/2023 • Accepted: 29/01/2024

CC BY-NC-ND 4.0 - This work is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License.

1. Introduction

Chest radiography (CXR) plays a crucial role in screening, triaging, diagnosing, evaluating, and monitoring patients. Its significance is demonstrated by the endorsement of the World Health Organization (WHO), which recommends its use for detecting conditions like pneumonia and tuberculosis [1]. Moreover, radiologists can examine various anatomical structures in the thoracic region, such as bones, soft tissues, lungs, mediastinum, cardiac lines or borders, and great vessels from the analysis of CXR, to name a few.

Computer-Aided Detection and Diagnosis (CADx) systems have become an increasingly important tool for diagnosing various diseases in modern medicine. For example, CADx systems commonly use the CXR as input to support the investigation of ribcage abnormalities such as cancers, tumors, pneumonia, chronic airway, diffuse lung, pleural and cardiac diseases, and traumas, among others.

The quality of radiographic images is critical in the de-

tection of abnormalities. These abnormalities are recognized through patterns such as consolidation, masses, nodules, lines, and cavities. To achieve this, various image preprocessing tasks, such as enhancement [2, 3, 4], foreign artifact detection [5, 6, 7], orientation correction [8, 9, 10] and segmentation [11, 12, 13] play essential roles, being critical components of these systems.

Image segmentation, in particular, involves separating an image into its constituent parts to identify regions of interest (ROI) that can help isolate and identify features indicative of specific conditions. This task is critical in interpreting CXR and increasing the reliability and quality of the system, reducing biases caused by noise in different parts of the ROI under analysis [14].

However, segmentation is a challenging task that constitutes one of the most complex processes in digital image processing [15]. In computational systems, mainly those that use radiological images, the precision of the segmentation

process is a fundamental step. Moreover, this task is even more challenging for these images due to their characteristics, such as low contrast between the ROI and other textures and the variations in lighting and acquisition conditions, to name a few [16].

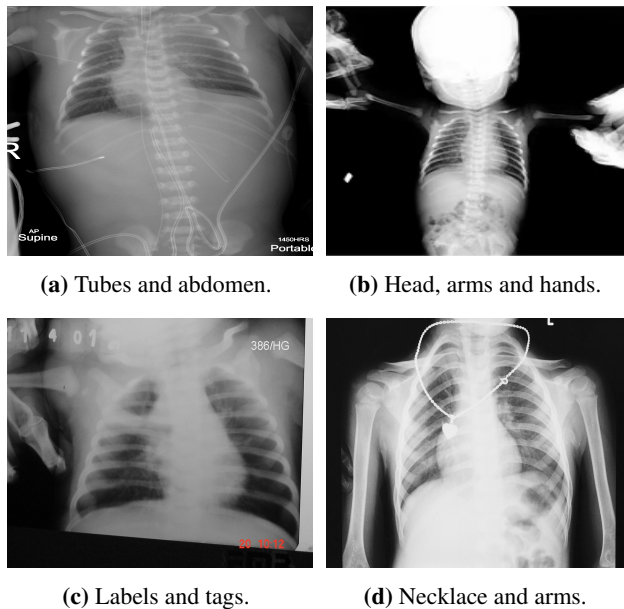


Figure 1. Foreign artifacts in public PCXR images.

Several CADx systems use segmented CXR images considering only the lung region. A consequence of this process is that certain regions necessary for analyzing other diseases detectable through X-rays are left out, such as the heart region necessary for diagnosing cardiomegaly, or the ribs, clavicle, and spine regions, which are essential to identify fractures and rotation patterns, for example. Thus, the segmentation encompassing the entire lung region represents an essential task with practical applications.

In addition, while automatic segmentation techniques are usually highly specialized based on the application, imaging modality, and analyzed body parts, they offer the benefit of reproducibility, which is difficult to achieve with manually defined results [17]. Consequently, researchers are continuously refining and developing new automatic segmentation techniques to enhance diagnostic accuracy in CADx systems and reduce the tediousness of manual segmentation processes, mainly when dealing with large datasets. This field of research remains active with numerous significant challenges to overcome [18, 19, 20].

In this sense, we propose an automated method for lung segmentation in pediatric CXR (PCXR) images to contribute to this area of research. Our proposal is based on the definition of an ROI corresponding to the outer limits of the ribcage region. Thus, all regions other than the thoracic one are discarded, avoiding undesirable effects in the analysis by CADx systems. In Figure 1, we present some examples of regions foreign to the thoracic region.

The main contributions of this study are:

- a new method for lung field segmentation based on rules and digital image processing;
- a low-cost and high-efficiency computational approach specially developed for PCXR images;
- an evaluation of the method in three traditional distance measures and a new proposed measure;
- performance analysis of the method for three distinct classes of pediatric X-ray images (normal, pneumonia, and indefinite).

The remainder of the paper is structured as follows. Section 2 presents related work to lung segmentation methods. Then, materials and methods are presented in Section 3, including information from the dataset and characteristics of the proposed method. Section 4 presents the experimental results and discussion and, finally, we present our conclusions and suggestions for future works in Section 6.

2. Related Work

Several studies on automated segmentation of medical images using deep learning have recently been published. The works' purposes are varied, establishing consistent alternatives for the segmentation of lungs, optic disc, and veins [16, 11, 21, 22], for example.

Shi *et al.* [11] and Fan *et al.* [12] addressed segmentation in CXR images in the context of COVID-19. The first reviews AI techniques for data acquisition, diagnosis, and segmentation, pointing out the importance of segmentation in aiding the diagnosis and quantification of injuries and the use of the *U-Net* [23] network as the primary model adopted. The latter developed a neural network model called *Inf-Net* to identify and segment virus-infected regions from chest CT slices.

Teixeira *et al.* [14] evaluated lung segmentation in CXR images' impact on diagnosing and explaining COVID-19. A greater power of generalization was pointed out for models that use segmentation about those that do not. In addition, segmentation forces models to look at the regions that matter, anxiously biasing and increasing the quality of interpreting and explaining models, as with activation maps. The authors also performed [24] lung segmentation to develop a robust COVID detection model on a small set of CXR images.

In [25], lung segmentation was used to analyze lesions and nodules suspected of cancer in CXR images and then combined and secondary with the inheritance of clavicle and rib shadows. The authors concluded that these techniques are essential in reducing overfitting and biases related to regions around the lungs.

Other research used traditional methods such as region, classification, grouping, graphic cutting, and models of active shapes, among others. The results achieved by these methods are helpful and a viable alternative for many cases. Below, we present some of these results found in the literature.

Li *et al.* [26] adopted a lung segmentation method based on statistical models of shape and appearance models. For

shape models, ‘multi-scale’ and ‘multi-steps-size’ with various constraint parameters were used. As for the appearance model, various features with different weights were used to describe the different parts of the lung field boundary.

In [27], various segmentation techniques for computerized analysis of CXR were described, while in [28, 29, 30, 31, 32] several method lung segmentation and improvement of CADx systems were covered.

Hogeweg *et al.* [33] segmented clavicles by pixel classification and Active Shape Model (ASM) employing dynamic programming with an optimized cost function. In [34], the authors evaluated the effect of reflexivity [35] in diagnosing common abnormalities in CXR.

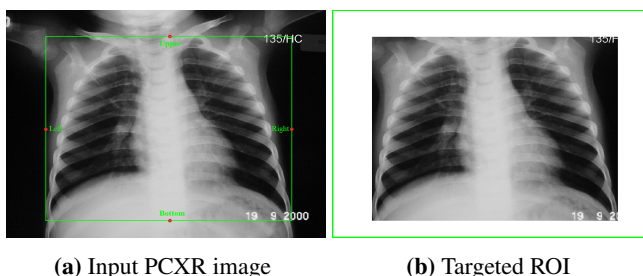
In [36], a straightforward algorithm for preprocessing CT images was described. The algorithm consists of two phases: mean filtering and morphological operations used to increase the performance of the segmentation process.

Doctor Iakovidis, professor and researcher at the University of Thessaly, Greece, proposed a model also based on ASM for detecting edges of lung fields in CXR images with the presence of lung immunity and acquired by portable RX devices [37]. Subsequently, this model was used to create a framework for pattern recognition, consisting of a hierarchical classifier, to measure the extent of pulmonary infiltrates in CXR images [38].

While these previous approaches focused on segmenting certain regions of the ribcage, such as lungs, ribs, and clavicle, our proposed segmentation method segments the entire ribcage, being tested and implemented for pediatric CXR images.

3. Material and Methods

Our proposal comprises a traditional method based on digital image processing operations and using rules to segment lung fields. To this aim, four points (left, right, upper, and bottom) are automatically identified and used to define the ROI corresponding to the ribcage region to be segmented. Figure 2 exemplifies the proposed method with all four reference points found automatically (Figure 2a), and the segmentation resulting from the process (Figure 2b).



(a) Input PCXR image (b) Targeted ROI
Figure 2. Defined ROI points and segmented final image.

The following subsections detail the database, the proposed method and the metrics used for evaluation.

3.1 Dataset

The Goiânia city health secretariat initiated vaccination against Hib in local health services in July 1999. A population surveillance system for community-acquired pneumonia admitted to pediatric hospitals in the city was implemented concurrently. Twenty pediatric hospitals participated in the study, which represents 85% of hospitalizations for pneumonia in the municipality. At hospital admission, a clinical-epidemiological record was completed and radiographs of all potential cases were photographed with high-resolution digital cameras (Mavica FD90) according to specifications and settings recommended by the World Health Organization (WHO) [39].

The digital photos were sent to two radiologists trained to interpret the radiographs according to standardized procedures during a workshop held in Santiago, Chile, sponsored by PAHO/WHO¹. Thus, “case of radiological pneumonia” was determined in the following situations: 1) the presence of alveolar opacity only; 2) the presence of any type of opacity (alveolar, interstitial or mixed) associated with pleural effusion; 3) Only pleural effusion.

The database contains about 23,000 images (85% of them on appropriate technical standards) from the CXR images of children under 5 years of age with clinical suspicion of pneumonia. They are in the RGB standard with 768 x 1024 pixels and stored in the JPEG format, making them an excellent digital collection for the construction of a specialized computer vision system. The database is stored in the Public Health Department of the Federal University of Goiás (IPTSP / UFG) [40]. Ethical approval for this research was granted by the Federal University of Goiás Ethics Committee, Goiânia, Brazil (protocol number 100/11).

To carry out an initial experiment to evaluate the proposal, we randomly selected 150 PCXR images from this dataset, equality distributed into 3 classes, labeled as ‘Bacterial’, ‘Normal’, and ‘Indefinite’, indicating cases with a confirmed diagnosis of bacterial pneumonia, normal or healthy cases, and cases without a determined diagnosis, respectively.

Then, we manually marked the 150 PCXR with 4 points, defining the ROI boundaries to be used as a reference for comparison with the proposed automatic method. The following subsections describe how our method automatically finds each point for defining the ROI.

3.2 Marking the Left and Right points

Left and right points that define the left and right boundaries of the ROI in the PCXR image are achieved by the following steps: i) Top-hat transform, ii) Binarization, iii) Selection of the two largest segments and iv) Definition of the left and right limits.

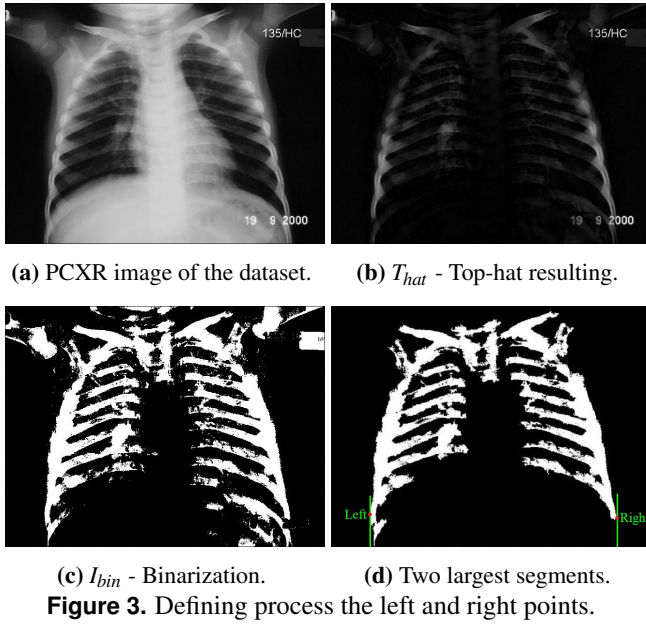
i) Top-hat transform: defined as $T_{hat}(f) = f - (f \circ b)$, where f is a grayscale image and $(f \circ b)$ is the morphological opening operation on this image f .

The Top-hat transformation is primarily used to remove

¹Pan American Health Organization/World Health Organization.

objects from an image, using a structuring element in the open operation and a subtraction operation to produce a new image where only the removed components remain. Thus, we use this transform with a disk of radius 32, empirically defined, as a structuring element.

This transform is often used to correct uneven lighting effects in images with light objects on a dark background. In our proposal, it was used to highlight the regions of greater density (more illuminated in the image) that correspond, respectively, to the bone structures of the thoracic cage. Figure 3a shows a PCXR image of our dataset and Figure 3b shows the result after applying the Top-hat transformation.



ii) Binarization: after taking the image T_{hat} resulting from the Top-hat transformation, a binarization operation is applied to this image as follows:

$$I_{bin}(x,y) = \begin{cases} 0 & \text{if } T_{hat}(x,y) < \mu(T_{hat}) * 1.25 \\ 1 & \text{if } T_{hat}(x,y) \geq \mu(T_{hat}) * 1.25 \end{cases} \quad (1)$$

where $\mu(T_{hat})$ is the average intensity of the image T_{hat} , x and y are the coordinates of the *pixels* of the image. The result $I_{bin}(x,y)$ is an image with the densest structures highlighted in white and the background in black, as shown in Figure 3c.

iii) Two largest segments: to eliminate small segments, such as those resulting from artifacts, we filtered the two largest segments of the binary image (I_{bin}). Thus, the left and right rib set is kept on the PCXR.

iv) Setting left and right points: taking the 2 largest segments, defining the left limit of the ROI (left point) is done by looking column by column for the first pixel with a value non-zero on the left, while defining the right limit of the ROI

(right point) by looking for the last pixel with a value non-zero, that is, the most to the right. The result is shown in Figure 3d.

3.3 Marking the Upper and Bottom points

Once the left and right points are defined, the PCXR image regions outside these limits are discarded (Figure 4a). Then we follow the definition of upper and bottom points, achieved by performing the following sequence of operations: i) Negative image via Otsu, ii) Valley definition, iii) Sum profile of the image lines, and iv) Definition of the upper and bottom points.

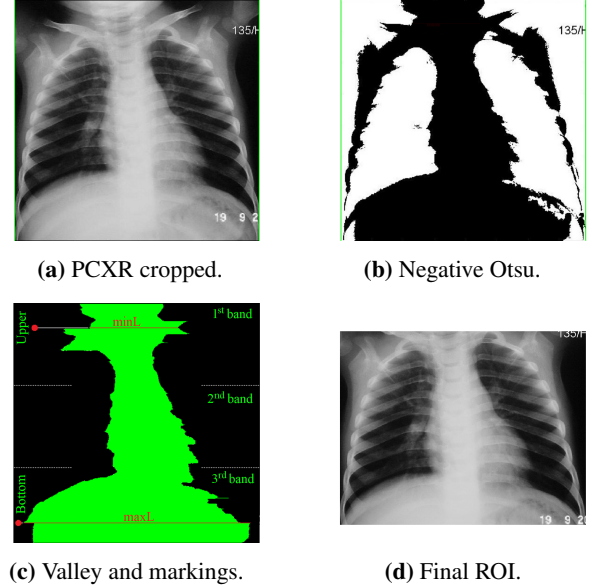


Figure 4. Definition of upper and bottom points.

i) Negative Otsu: Otsu thresholding is a method that determines an ideal threshold for separating an image into two parts, corresponding to the 'front' and the 'background' of the image. In this, the lightest regions of the image are set to a value equal to 1 ('front'), and the darkest regions are set to a value equal to 0 ('background'). The negative is the process that inverts these values in the image.

ii) Valley finding: the valley corresponds to the central region of the PCXR highlighted in green in Figure 4c. This region is found by a process that starts in the central columns of the PCXR (mediastinal approximation) and moves from left to right until it finds a point in the image with value 1 (white pixel). Once the valley is defined, the image is divided into three horizontal bands of the same size. From there, you find the location of a shorter line in the top band of the image and a longer one in the down band.

iii) Horizontal profile: this profile is a count of the number of white pixels in each of the lines in the PCXR image. This value evaluates the percentage of the image considered as 'background' by the thresholding process, step i). Unlike the analysis of valley lines, the horizontal profile of the image allows for recovering information from discontinuous

background regions, which is impossible with valley lines.

iv) Setting upper and bottom points: these points are defined by evaluating the length of the valley lines and the horizontal profile, observing the following rules:

a) the upper point must be in 1st band and the bottom point in 3rd band of the PCXR image.

b) an outside safety margin of 64 pixels must be added concerning the upper and bottom points found.

c) the height/width ratio must be less than 85%. The cardiac contour in PCXR images is up to 60% larger than the thorax's horizontal diameter [41], resulting in a slightly rectangular ROI. We also verified similar standards in our manual pick-up, ranging the height from 41.2% to 84.8% of the width of PCXR images.

Thus, the upper point is defined by looking from the first line: An occurrence with length $\geq 90\%$ of the longest line in the valley and less than 20% of the height of the PCXR image. If it does not exist, it searches the horizontal profile for the first occurrence whose value is $\geq 80\%$ of the width of the PCXR image, and if the upper point does not exist, it will be the first of the valley line with the minimum length.

The bottom point is defined by looking in the 3rd band for the first occurrence of a line with the maximum length between the lines in the valley.

After defining the upper and bottom points of the ROI, the outer regions are removed and rule c) is checked. If this rule is not met, new looking is performed until all restrictions are met. Figure 4c show the valley, bands, and the upper and bottom points delimit the ROI on this PCXR image, while Figure 4d shows the final ROI defined for the method.

3.4 Evaluation Measures

The proposed method was evaluated considering four distance measures: Dice similarity coefficient (DSC), Hausdorff Distance (HD), Jaccard or Intersection over Union (IoU) [42]. We also proposed an accuracy scale distance (ACC_i), shown in detail here. To do so, each of the 150 PCXR images mentioned in Subsection 3.1 is compared to its ground truth region of interest (ROI). Here, we define image A) as the ground truth ROI from the points manually defined as a reference and image B) as the predicted ROI from the points automatically obtained by the method. Each measure is explained next.

Our precision scale-based measure considers the distance of the points found by the proposed method in relation to the manually defined reference points. When defining this scale, the average height of the ribs was considered, reaching a value of 32 *pixels*. This value is used because it is an acceptable tolerance in defining the ROI, since the lung apices are above the first rib.

The accuracy is then tabulated at three levels, shown in Figure 5. The method reaches level zero when no distance greater than 32 pixels of ground truth is detected. The positive points of the scale (+1, +2, or +3) represent the number of

points detected beyond the reference limits or, equivalently, the false positives. Finally, the negative points of the scale (-1, -2, or -3) represent the points detected below the reference limits, corresponding to false negatives. Equation 2 shows how to calculate this accuracy measure.

$$ACC_i(A,B) = \frac{\sum_{n=1 \rightarrow N} d(a,b)}{\lceil 32iN \rceil} \quad (2)$$

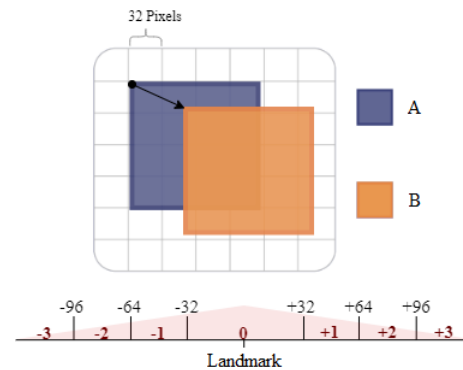


Figure 5. ACC_i graphic representation.

4. Results and Discussion

Table 1 presents the values obtained for the method to DSC, IoU, HD, and also in our ACC_0 and ACC_1 accuracy scales. The results presented correspond to the ROI analysis for each of the three classes of PCXR images – ‘normal’, ‘bacterial’, and ‘indefinite’.

Table 1. Assessment of the Method Result

Metrics	Image Class			TOTAL
	Normal	Bacterial	Indefinite	
DSC	0.96±0.03	0.96±0.03	0.96±0.02	0.96±0.03
IoU	0.92±0.05	0.92±0.05	0.93±0.04	0.92±0.05
ACC_0	0.79±0.04	0.82±0.04	0.84±0.04	0.82±0.04
ACC_1	0.97±0.09	0.94±0.09	0.98±0.10	0.96±0.09
HD	6.42±7.54	6.64±7.24	5.31±6.74	6.12±7.17

DSC and IoU are two widely used metrics to evaluate the similarity between two sets of data, in this case, the predicted and ground truth masks of the three classes of PCXR images. The results show that the method has achieved excellent overall performance with average DSC values of 0.96 ± 0.03 and IoU values ranging from 0.92 ± 0.05 to 0.93 ± 0.04 . These high values indicate that the predicted masks are highly similar to the ground truth masks, and the method is accurate in segmenting the three classes of PCXR images.

The following two metrics, ACC_0 and ACC_1 accuracy scales measure the overall accuracy of the method in predicting the three classes of PCXR images. ACC_0 measures a maximum distance of 32 pixels between the predicted mask and the

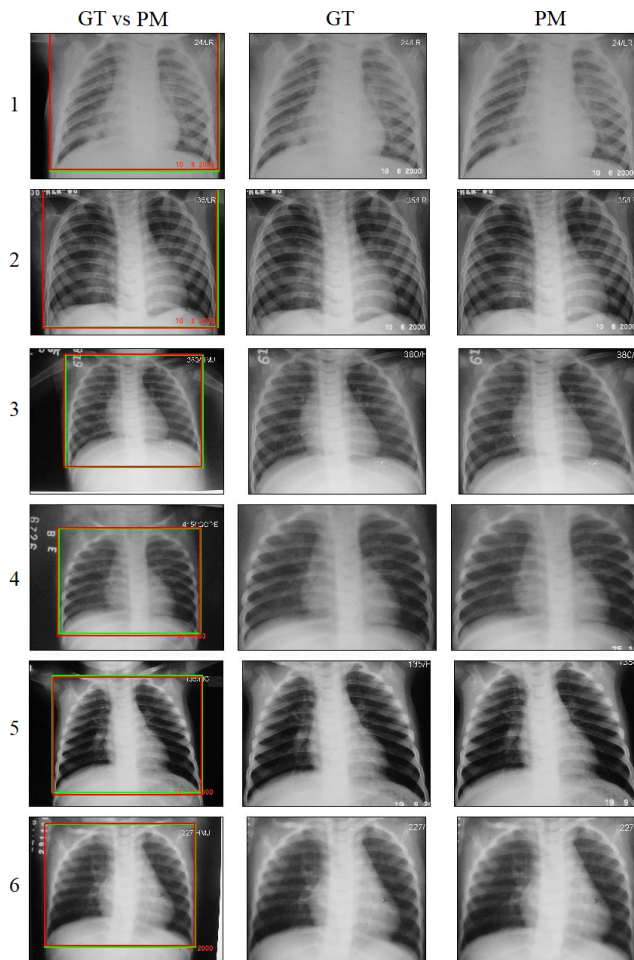


Figure 6. The ground truth ROI boundary (GT) is depicted in green, and the automatically segmented ROI boundary by our proposed method (MP) is presented in red color. Images 1-2, 3-4, and 5-6 are Bacterial, Normal, and Indefinite classes, respectively.

ground truth, while ACC_1 measures 33-64 pixels. The results show that the method reached an ACC_0 range of 0.79 ± 0.04 to 0.84 ± 0.04 and an ACC_1 range of 0.84 ± 0.09 to 0.98 ± 0.10 . The lower ACC_0 values are explained by corresponding to the ‘perfect’ overlap between the ground truth and the prediction. The DSC and ACC_1 values are the most relevant, as they tend to measure something closer to the average performance, while the IoU penalizes the generated errors to a greater degree.

Lastly, HD is a metric that measures the maximum distance between predicted and actual ROI. The results show that the method has an HD range of 5.31 ± 6.74 to 6.64 ± 7.24 , indicating that the maximum distance between the predicted and actual ROI is relatively tiny, also observed by ACC_0 . Thus, these results and DSC and IoU values suggest that the method achieved high accuracy and similarity between predicted and ground truth ROI.

Figure 6 shows some comparisons between the ground

truth ROI (green lines) and that predicted by the proposed method (red lines). These results reinforce what is seen in Table 1, that the prediction performance of the method is unaffected by the image class.

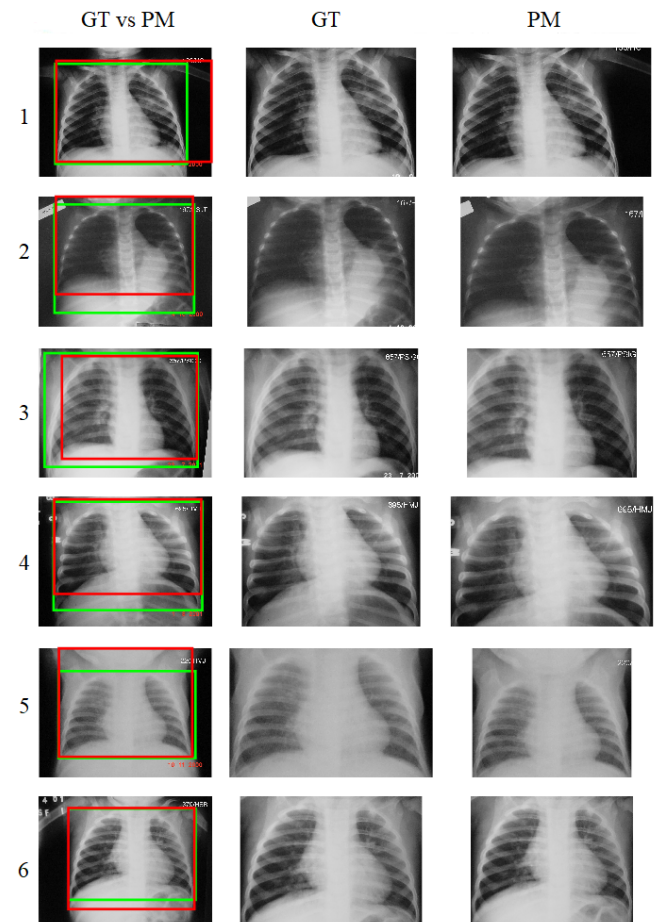


Figure 7. Worst results – The ground truth ROI boundary (GT) is depicted in green, and the automatically segmented ROI boundary by our proposed method (MP) is presented in red color. Images 1-2, 3-4, and 5-6 are Bacterial, Normal, and Indefinite classes, respectively.

Figure 7 shows the cases where our method fails in an accurate prediction. We attribute these failures partly to poor-quality images with the excessive presence of foreign artifacts, lack of contrast, and improper acquisition or scanning process handling.

Further analysis of the four detected points is also shown in the graphs in Figure 8, with the frequency of each of the four points on our accuracy scale divided by PCXR image classes. These graphs show that the definition of the left and right limits are better resolved (average accuracy 95% for level 0) compared to the upper and bottom points (average accuracy of 68.3% for level 0), pointing to the method’s difficulty in identifying the latter. This difficulty can be explained by the low quality of the images (low resolution and contrast), which

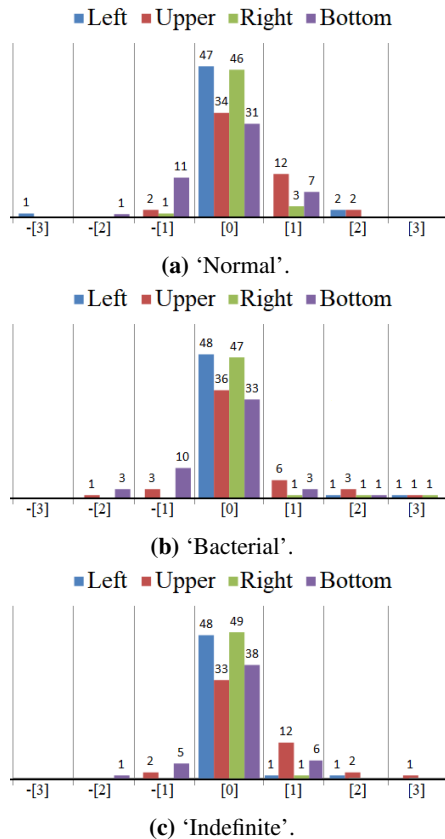


Figure 8. An analysis of the four points detected on our accuracy scale, divided into PCXR image class.

sometimes makes it impossible to identify the pulmonary apexes (which define the upper point) and the costophrenic sinuses (which define the bottom point).

The inferior performance in the images of the 'Bacteria' class is expected and justifiable since the images of this class present infiltration, impacting both the definition of edges and the threshold. In this class, the method has the largest number of points detected in levels 2 and 3 of our accuracy scale.

Another important observation is that only one point (Left) was detected at level -3 accuracy scale, shown in the line 3 image of Figure 7. Thus, the technique presents high sensitivity, with little loss of the desirable ROI, which can also be observed in the results presented in Figure 6.

Table 2 brings a comparison with other chest X-ray segmentation studies. Although most of the previous studies in the literature performed segmentation of the lungs differently from our method, which segmented the entire thoracic cage, a comparison is still engaging in qualitatively positioning our results against prior studies. The studies vary significantly on the model and dataset used, as well as in terms of image resolution, inference time, training mode (supervised or semi-supervised), and GPU usage. Some pros and cons of each previous work are also indicated.

Among the listed studies, Li et al. [26] achieved high precision in the segmentation process using SSM and SAM models

in the JSRT dataset. However, the performance of the models is conditional on a longer training time and samples. Vidal et al. [43] achieved robust performance using a UNET model with transfer learning on the COVID-19 dataset, which had the advantage of portable images. However, this approach had a lower IoU and required prior learning. Al-Eiadeh [45] used the DeepLabv3 and ResNet-18 models on the Montgomery dataset, which achieved high accuracy but had high computational complexity and a higher risk of overfitting. Chavan et al. [47] used a ResUNET++ model on the Montgomery dataset, which also performed robustly, but lower-resolution images were used.

Meanwhile, our method uses a rule-based model and digital image processing on a private dataset of pediatric chest images. As a result, fast and accurate segmentation is achieved without requiring any training step, and reasonable IoU and significant DSC are obtained compared to other studies. Each study has strengths and limitations, depending on the specific dataset and study requirements. Therefore, it is essential to carefully consider the tradeoffs between accuracy, speed, and complexity when choosing an appropriate targeting model for a specific application.

Finally, as proposed in this work, we highlight the importance of segmenting the thoracic region to aid lung segmentation, as reported in [48, 49, 50]. Hence, the method proposed here can serve as an essential tool to segment other regions of interest within the thoracic region, such as the lungs, heart, and clavicle, by reducing the original size images (approximately 26.75%) to be analyzed. In addition, segmenting the thoracic region may also increase the accuracy of other classification methods, such as those focused on diagnosing lung diseases.

5. Limitations

Despite the promising performance exhibited by the proposed method in our experiments, it is imperative to acknowledge and address certain inherent limitations. Firstly, the robust parameterization of the technique may limit its adaptability to the intrinsic variability of pediatric images and its responsiveness to diverse scenarios. While this parametric rigidity has been applied to mitigate variability, questions arise regarding its effectiveness in the face of more heterogeneous scenarios.

Another point of consideration lies in the sample size, which is limited to 150 images due to human, material, and temporal resource constraints. Despite an observed equitable distribution among classes and variability among acquisition equipment, it is crucial to recognize the potential limitation in generalizing results due to the restricted sample size. Finally, it is essential to highlight that the proposal remains experimental, requiring further in-depth analyses and extensive testing for a more comprehensive understanding of its impact. This experimental nature, however, does not diminish the significance of the obtained results but underscores the need for future investigations to consolidate the contributions of the proposed method.

Table 2. Qualitative comparison with chest X-ray segmentation studies in the literature.

Study	Model	Dataset	Image	Time	Mode	GPU	DSC	IoU	HD	Pros	Cons
[43]	UNET w/ Transfer learning	COVID	256×256	-	S	Y	0.944±0.024	0.894±0.042	-	Portable images, robust performance	Lower IoU and Requires previous learning
[26]	SSM, SAM	JSRT	1024×1024	40s	S	N	0.964±0.010	0.931±0.018	-	High accuracy	Requires longer training time and larger samples
[44]	FCNN	Private	512×512	-	S	-	0.870±0.040	-	-	Customized, relatively low complexity	Lower DSC
[45]	DeepLabv3 and ResNet-18	Montgomery	256×256	-	S	Y	0.969	0.941	-	High accuracy	High computational complexity, overfitting risk
[46]	UNET (FVAE+TTAM)	JSRT	512×512	0.45 s	S	Y	-	0.9201	-	Fast inference time	May require larger training datasets, lower IoU
[47]	ResUNET++	Montgomery	256×256	-	S	Y	0.959	0.937	-	Robust performance	Lower resolution images
Our	Rules and DIP	Private	768×1024	0.81 s	SS	N	0.960±0.030	0.920±0.050	6.12±7.17	Fast and accurate, unrequired training	Lower IoU

Note: The training mode refers to **S**: Supervised - using annotated data or **SS**: Semi-Supervised - a combination of annotated and unannotated data. **DIP**: Digital Image Processing.

6. Conclusion

This article presents a straightforward and effective method for segmenting regions of interest (ROI) in chest X-ray images. The proposed approach was tested and evaluated on a PCXR image dataset from our institution. The experimental results were presented using a set of appropriate evaluation metrics over images from three distinct classes - ‘normal’, ‘bacterial’, and ‘indefinite’. Our solution boasts impressive performance, easy implementation, and low computational complexity. Furthermore, it does not necessitate training steps, which can be seamlessly integrated into preprocessing steps in more complex CADx models and systems workflows.

Acknowledgements

This study was financed in part by the CAPES - Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil - Finance Code #001. The authors would also like to thank the Federal Institute Goiano for supporting this research.

Author contributions

Afonso Ueslei da Fonseca: Conceptualization, Methodology, Visualization, Software, Writing - Original Draft. Juliana Paula Felix: Methodology, Formal Analysis, Writing - Original Draft. Gabriel da Silva Vieira: Methodology, Writing - Reviewing. Deborah Fernandes: Formal Analysis. Fabrizzio Soares: Supervision.

References

- [1] ORGANIZATION, W. H. et al. *Chest radiography in tuberculosis detection: summary of current WHO recommendations and guidance on programmatic approaches*. [S.l.], 2016.
- [2] NEFOUSSI, S.; AMAMRA, A.; AMAROUCHE, I. A. A comparative study of chest x-ray image enhancement techniques for pneumonia recognition. In: SPRINGER. *Advances in Computing Systems and Applications: Proceedings of the 4th Conference on Computing Systems and Applications*. [S.l.], 2021. p. 276–288.
- [3] FONSECA, A. U. et al. X-ray image enhancement: A technique combination approach. In: *2019 IEEE 31st International Conference on Tools with Artificial Intelligence (ICTAI)*. [S.l.: s.n.], 2019. p. 1686–1690.
- [4] RUI, W.; GUOYU, W. Medical x-ray image enhancement method based on tv-homomorphic filter. In: IEEE. *2017 2nd International Conference on Image, Vision and Computing (ICIVC)*. [S.l.], 2017. p. 315–318.
- [5] ROY, S.; SANTOSH, K. Analyzing overlaid foreign objects in chest x-rays—clinical significance and artificial intelligence tools. In: MULTIDISCIPLINARY DIGITAL PUBLISHING INSTITUTE. *Healthcare*. [S.l.], 2023. v. 11, n. 3, p. 308.
- [6] MEYER, T. J. et al. Systematic analysis of button batteries’, euro coins’, and disk magnets’ radiographic characteristics and the implications for the differential diagnosis of round radiopaque foreign bodies in the esophagus. *International Journal of Pediatric Otorhinolaryngology*, v. 132, p. 109917, 2020.
- [7] FONSECA, A. U. et al. Foreign artifacts detection on pediatric chest x-ray. In: IEEE. *2020 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE)*. [S.l.], 2020. p. 1–4.
- [8] FONSECA, A. et al. Automatic orientation identification of pediatric chest x-rays. In: *2020 IEEE 44th Annual Computers, Software, and Applications Conference (COMPSAC)*. [S.l.: s.n.], 2020. p. 1449–1454.

- [9] Reza, S.; Amin, O. B.; Hashem, M. M. A. A novel feature extraction and selection technique for chest x-ray image view classification. In: *2019 5th International Conference on Advances in Electrical Engineering (ICAEE)*. [S.l.: s.n.], 2019. p. 189–194.
- [10] SANTOSH, K.; WENDLING, L. Angular relational signature-based chest radiograph image view classification. *Medical & biological engineering & computing*, Springer, v. 56, n. 8, p. 1447–1458, 2018.
- [11] SHI, F. et al. Review of artificial intelligence techniques in imaging data acquisition, segmentation, and diagnosis for covid-19. *IEEE Reviews in Biomedical Engineering*, v. 14, p. 4–15, 2021. ISSN 1941-1189.
- [12] FAN, D.-P. et al. Inf-net: Automatic covid-19 lung infection segmentation from ct images. *IEEE Transactions on Medical Imaging*, v. 39, n. 8, p. 2626–2637, Aug 2020. ISSN 1558-254X.
- [13] FONSECA, A. U.; FELIX, J. P.; SOARES, F. Segmentação da região pulmonar em radiografias pediátricas de tórax. In: *SBC. Anais da X Escola Regional de Informática de Goiás*. [S.l.], 2022. p. 48–59.
- [14] TEIXEIRA, L. O. et al. Impact of lung segmentation on the diagnosis and explanation of covid-19 in chest x-ray images. *arXiv preprint arXiv:2009.09780*, 2020.
- [15] GONZALEZ, R. C.; WOODS, R. E. *Processamento digital de imagens*. 3. ed. [S.l.]: Pearson Prentice Hall, São Paulo, 2010.
- [16] TAHERI, M.; RASTGARPOUR, M.; KOOCHARI, A. A novel method for medical image segmentation based on convolutional neural networks with sgd optimization. *Journal of Electrical and Computer Engineering Innovations (JECEI)*, Shahid Rajaei Teacher Training University, v. 9, n. 1, p. 37–46, 2021.
- [17] CLARKE, L. et al. MRI segmentation: methods and applications. *Magnetic resonance imaging*, Elsevier, v. 13, n. 3, p. 343–368, 1995.
- [18] CHEN, J. et al. Transunet: Transformers make strong encoders for medical image segmentation. *arXiv preprint arXiv:2102.04306*, 2021.
- [19] HESAMIAN, M. H. et al. Deep learning techniques for medical image segmentation: achievements and challenges. *Journal of digital imaging*, Springer, v. 32, n. 4, p. 582–596, 2019.
- [20] ZHOU, Z. et al. Unet++: A nested u-net architecture for medical image segmentation. In: *Deep learning in medical image analysis and multimodal learning for clinical decision support*. [S.l.]: Springer, 2018. p. 3–11.
- [21] MAHMOOD, F. et al. Deep adversarial training for multi-organ nuclei segmentation in histopathology images. *IEEE Transactions on Medical Imaging*, v. 39, n. 11, p. 3257–3267, Nov 2020. ISSN 1558-254X.
- [22] GU, Z. et al. Ce-net: Context encoder network for 2d medical image segmentation. *IEEE Transactions on Medical Imaging*, v. 38, n. 10, p. 2281–2292, Oct 2019. ISSN 1558-254X.
- [23] RONNEBERGER, O.; FISCHER, P.; BROX, T. U-net: Convolutional networks for biomedical image segmentation. In: *SPRINGER. International Conference on Medical image computing and computer-assisted intervention*. [S.l.], 2015. p. 234–241.
- [24] OH, Y.; PARK, S.; YE, J. C. Deep learning covid-19 features on cxr using limited training data sets. *IEEE transactions on medical imaging*, IEEE, v. 39, n. 8, p. 2688–2700, 2020.
- [25] GORDIENKO, Y. et al. Deep learning with lung segmentation and bone shadow exclusion techniques for chest x-ray analysis of lung cancer. In: *SPRINGER. International Conference on Computer Science, Engineering and Education Applications*. [S.l.], 2018. p. 638–647.
- [26] LI, X. et al. Automatic lung field segmentation in x-ray radiographs using statistical shape and appearance models. *Journal of Medical Imaging and Health Informatics*, v. 6, n. 2, p. 338–348, 2016. ISSN 21567018.
- [27] GINNEKEN, B. V. *Computer-aided diagnosis in chest radiography*. Tese (Doutorado) — University Medical Center Utrecht, 6 2001.
- [28] PENG, T. et al. Hybrid automatic lung segmentation on chest ct scans. *IEEE Access*, IEEE, v. 8, p. 73293–73306, 2020.
- [29] CANDEMIR, S.; ANTANI, S. A review on lung boundary detection in chest x-rays. *International journal of computer assisted radiology and surgery*, Springer, v. 14, n. 4, p. 563–576, 2019.
- [30] CANDEMIR, S.; JAEGER, S. et al. Lung segmentation in chest radiographs using anatomical atlases with nonrigid registration. *IEEE Transactions on Medical Imaging*, v. 33, n. 2, p. 577–590, 2014. ISSN 02780062.
- [31] JAEGER, S. et al. Automatic screening for tuberculosis in chest radiographs: a survey. *Quantitative imaging in medicine and surgery*, v. 3, n. 2, p. 89–99, 2013. ISSN 2223-4292.
- [32] XUE, Z. et al. Foreign object detection in chest x-rays. In: *IEEE. Bioinformatics and Biomedicine (BIBM), 2015 IEEE International Conference on*. [S.l.], 2015. p. 956–961.
- [33] HOGEWEG, L. et al. Clavicle segmentation in chest radiographs. *Medical Image Analysis*, Elsevier B.V., v. 16, n. 8, p. 1490–1502, 2012. ISSN 13618415. Disponível em: <http://dx.doi.org/10.1016/j.media.2012.06.009>.
- [34] SCHALEKAMP, S. et al. The effect of supplementary bone-suppressed chest radiographs on the assessment of a variety of common pulmonary abnormalities: Results of an observer study. *Journal of thoracic imaging*, LWW, v. 31, n. 2, p. 119–125, 2016.

- [35] HOGEWEG, L.; SANCHEZ, C. I.; Van Ginneken, B. Suppression of translucent elongated structures: Applications in chest radiography. *IEEE Transactions on Medical Imaging*, v. 32, n. 11, p. 2099–2113, 2013. ISSN 02780062.
- [36] PATIL, S.; UDUPI, D. V. Preprocessing to be considered for mr and ct images containing tumors. *IOSR Journal Electrical and Electronics Engineering*, v. 1, n. 4, p. 54–57, 2012.
- [37] IAKOVIDIS, D. K.; SVELONAS, M. A.; PAPAMICHALIS, G. Robust model-based detection of the lung field boundaries in portable chest radiographs supported by selective thresholding. *Measurement Science and Technology*, v. 20, n. 10, p. 104019, 2009. ISSN 0957-0233.
- [38] TSEVAS, S.; IAKOVIDIS, D. K. Measuring the relative extent of pulmonary infiltrates by hierarchical classification of patient-specific image features. *Measurement Science and Technology*, v. 22, n. 11, p. 114017, 2011. ISSN 09570233.
- [39] ANDRADE, A. L. S. S. de et al. Effectiveness of haemophilus influenzae b conjugate vaccine on childhood pneumonia: a case-control study in brazil. *International journal of epidemiology*, Oxford University Press, v. 33, n. 1, p. 173–181, 2004.
- [40] FONSECA, A. U.; OLIVEIRA, L. L. G.; SOARES, F. A. A. M. N. Detecção de artefatos estranhos em radiografias de tórax. In: *XV CBIS- Congresso Brasileiro de Informática em Saúde*. Goiânia, Brasil: [s.n.], 2016. p. 721–730.
- [41] CANDEMIR, S.; ANTANI, S. et al. Lung boundary detection in pediatric chest x-rays. In: *Proc. SPIE, Medical Imaging 2015: PACS and Imaging Informatics: Next Generation and Innovations*. [S.l.: s.n.], 2015. v. 9418, p. 94180Q–94180Q–6.
- [42] REINKE, A. et al. Understanding metric-related pitfalls in image analysis validation. *arXiv preprint arXiv:2302.01790*, 2023.
- [43] VIDAL, P. L. et al. Multi-stage transfer learning for lung segmentation using portable x-ray devices for patients with covid-19. *Expert Systems with Applications*, Elsevier, v. 173, p. 114677, 2021.
- [44] HUYNH, H. T.; ANH, V. N. N. A deep learning method for lung segmentation on large size chest x-ray image. In: *2019 IEEE-RIVF International Conference on Computing and Communication Technologies (RIVF)*. [S.l.: s.n.], 2019. p. 1–5.
- [45] AL-EIADEH, M. R. Automatic lung field segmentation using robust deep learning criteria. *International Journal of Hybrid Innovation Technologies*, v. 1, n. 1, p. 69–82, 2021.
- [46] CAO, F.; ZHAO, H. Automatic lung segmentation algorithm on chest x-ray images based on fusion variational auto-encoder and three-terminal attention mechanism. *Symmetry*, MDPI, v. 13, n. 5, p. 814, 2021.
- [47] CHAVAN, M. et al. Deep neural network for lung image segmentation on chest x-ray. *Technologies*, MDPI, v. 10, n. 5, p. 105, 2022.
- [48] RAJARAMAN, S. et al. Comparing deep learning models for population screening using chest radiography. In: *SPIE. Medical Imaging 2018: Computer-Aided Diagnosis*. [S.l.], 2018. v. 10575, p. 322–332.
- [49] SRIMATHI, D. H.; ROSE, D. P. et al. A Comparative Study On Performance Of Pre-Trained Convolutional Neural Networks In Tuberculosis Detection. *European Journal of Molecular & Clinical Medicine*, v. 7, n. 3, p. 4852–4858, 2020.
- [50] RAJARAMAN, S. et al. Improved semantic segmentation of tuberculosis—Consistent findings in chest x-rays using augmented training of modality-specific U-Net models with weak localizations. *Diagnostics*, Multidisciplinary Digital Publishing Institute, v. 11, n. 4, p. 616, 2021.