Lung Field Segmentation in Chest X-Rays Using Snake Segmentation Approach with Normalized Gradient Gaussian Filter

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Abstract: The segmentation of lung fields in chest X-ray images is one of the most significant preliminary steps in the process of pulmonary analysis. This step allows for the identification of specific lung fields. This article's objective is to present a method for the segmentation of the lung field that makes use of a mix of image processing techniques and MATLAB implementation. Our solution takes use of the Gaussian filter with normalized gradient in conjunction with Snake or active contour segmentation, which brings about a significant improvement in edge recognition while also lowering the amount of time required for processing. In the course of digital chest X-ray scans, this method is quite effective in distinguishing between the various parts of the lungs. As a result, it is much simpler to recognize breakpoints in the lung field. With the support of this crucial step, the subsequent careful examination of lung illnesses is made simpler and more likely to be successful. The invention of these technologies can be traced back to the middle of the 1960s, and they are still being worked upon in order to obtain more precise demarcation of the lung region and measurement of the breakpoint temperature than they were previously capable of. As a result of our findings, it would appear that a combination method is more suitable for both the existing developments in lung field segmentation in computed tomography (CXR) pictures as well as the developments that are expected to occur in the future.

Keywords- Lung Field Segmentation, Chest X-Ray Analysis, Gaussian Filter, Snake or active contour segmentation Method, Digital Radiography.

Introduction:

Chest radiography, commonly known as a chest X-ray, is one of the most significant diagnostic instruments in the world of medical imaging. The fundamental objective of this procedure is to provide assistance in the diagnosis of lung diseases and the identification of abnormalities. Over the course of its history, this technology has undergone significant advancements, and it has finally become an essential component in the process of diagnosing and treating pulmonary problems in patients who are suffering from those illnesses. In light of the methodology that is being explained, it is now clearly evident that the preprocessing stage of evaluating chest radiographs, and more specifically the segmentation of lung sections, is a critical phase in the process. This is the case since the preprocessing stage involves the segmentation of lung sections. Not only does the exact segmentation of lung fields help medical personnel save time, but it also enhances their capacity to diagnose lung diseases with more precision, which is a key component of providing quality care to patients [1].

In addition to the straight forward identification of the multiple components that make up the lungs, the significance of lung field segmentation extends somewhat further than that. The reason for this is that the lungs are made up of a variety of different components. In the case of chest X-rays, some examples of anatomically exact images that can be obtained with their aid are the enhancement of the lung region and the exclusion of bone structures. The samples that are provided here are both very good examples. This particular phase is among the most essential ones that require to be carried out in the process. This segmentation makes it feasible to perform an analysis that is both more accurate and more detailed. This is because it enhances the capacity to distinguish between the various parts that comprise the lungs. This approach holds great significance in the early diagnosis of lung illnesses. This is because potentially concerning lung finds can remain undetected in the absence of precise segmentation. This impact would arise because the lung would be divided into smaller sections. By examining this specific justification, one can determine the applicability of this procedure [2].

Over time, incredible progress has been made in the segmentation procedures, leading to numerous discoveries. In addition, a wide range of methods have been developed in order to arrive at an accurate determination of the boundaries of lung fields. There are a broad variety of complex image processing techniques that are typically utilized by these systems. Some examples of these approaches include contrast enhancement, edge detection, area merging, and completion [3]. When it comes to distinguishing between the distinct lung sectors, the utilization of these procedures is an unquestionably necessary prerequisite. When the segmentation process is finished, they also lay the framework for a full evaluation of the lung health that will be carried out. This examination will take place once the segmentation procedure has been done.

A technique that is considered to be one of the most essential components of image processing is the method of extracting power profiles and regions from anatomical structures. Taking this into consideration, this is one of the most significant characteristics. Several different methods of image processing make substantial use of these profiles, which can be derived from a wide variety of anatomical characteristics. There are numerous uses for these profiles. These profiles are extremely significant for many different image processing techniques and are also incredibly valuable. Lung field segmentation is a multifaceted process that requires the application of many techniques. Techniques that come within this category include graph cuts, artificial intelligence-based algorithms, and dynamic shape models [4]. This activity is carried out in order to carry out specific operations in an efficient and effective manner.

In earlier times, lung field segmentation techniques were developed using radiographs showing normal or somewhat disturbed lung conditions. These datasets are used as a starting point for investigations and the creation of improved segmentation methods [5]. Nonetheless, there is an increasing need for rigorous approaches that identify problems in the lung areas more quickly and accurately [6]. Recently, computed tomography (CT) imaging has emerged as a key technique for achieving these segmentation goals because it provides comprehensive three-dimensional information about the lungs within this framework [7].

Considering the aforementioned, the goal of this study is to investigate the degrees of difficulty related to lung field segmentation in chest radiography [8]. To be more specific, the study will concentrate on dividing the lung field into sections. Within the parameters of the examination, the primary emphasis will be made on the many different procedures and procedures that are put into place. In this work, we are going to provide a thorough analysis of the suggested segmentation strategy, which combines snake segmentation approach and Gaussian filter with normalized gradient. Part of this is the focus of this study because this technique makes use of active contours at the appropriate times, thus it remains very significant. This is one of the big pluses that make this technique so prominent [9]. Concerning this technique, which effectively segments lung fields using active contours, is quite noteworthy. In addition, we will discuss the need of dividing the lung field into distinct sections and use relevant images for analysis and demonstration. Moreover, the conclusion section will highlight the key information that is thought to be the most pertinent in this sector which will also look at how important these results are for chest radiography [10].

Recently, several approaches have been devised to improve lung segmentation techniques from medical images. One of the landmark efforts was creating a modified UNet++ model that enhances the accuracy of lung segmentation from chest X-ray images and showed marked improvements over previous models. Complementing this, another study implemented an advanced method for instance segmentation to precisely identify anatomical structures in chest radiographs and added to the gamut of medical image analysis [11-13]. The challenge of pathological lung segmentation was mooted with the application of comprehensive image data augmentation techniques and significantly improved the performance of deep learning models. In a different approach, it combined medical image processing with machine learning to achieve robust and reliable lung segmentation and attested to the symbiosis of these technologies [14-15].

An innovative method integrating 3D appearance and surface models was introduced, thereby achieving accurate segmentation of pathological lungs and emphasizing the importance of integrating multi-dimensional data [16]. Next, the SMR-UNet algorithm was devised specifically for effective lung nodule segmentation, and it highlighted the need for specialized algorithms when dealing with medical imaging tasks [17]. Finally, the Med Net algorithm was developed to improve the accuracy of segmentation for lung cancer diagnosis and was a positive step toward more accurate and reliable diagnostic tools in medical imaging [18]. In this way, as we advance and, at the same time, refine these procedures, it is becoming evident that there is a need for the use of segmentation approaches which not only work but also have the capability of making precise identification and analysis of any anomalies within lung areas. The requirement keeps on growing, as we go on constantly bettering and enhancing them. With the continuous work towards the improvement of these procedures, the need becomes more obvious. The imaging technology, CT notably computed tomography, which provides 3D information on lungs, is a potential solution towards these goals. This is true because of the remarkable breakthroughs that have been made in the area of medical imaging and lung disease diagnosis.

Gaussian filter with normalized gradient with Snake or active contour segmentation Approach:

The process of smoothing the image and reducing the amount of noise in the final image should generally help in improving the detection of edges on lung field regions. The Gaussian filter with normalized gradients is the code name for this filter. A Gaussian distribution helps in achieving the goal of normalizing the magnitudes of the gradients. This distribution helps in preserving the finer details of the lung borders while reducing the distortion that is created by picture components not related to each other. Snake or active contour segmentation technique is iterative. The procedure, generally called active contour modeling, is needed to get fit a spline, sometimes known as snake, within the limitations of the lungs. Because this method can in particular conform to the shapes and curves of the lungs that an X-ray captures, it is predominantly effective in segmenting the complex architecture of the lungs. For the reason that of its adaptability, the snake model can specifically portray the internal organs and lung limits, allowing it to account for anatomical variations in various patients. Putting these two strategies together has a synergistic impact. The image undergoes preprocessing with a Gaussian filter with a normalized gradient to perk up edge clarity. This means that during the segmentation process, it will be easier for the snake model to converge in a way that is both more accurate and efficient. The fact that this all-encompassing technique is tuned for both speed and accuracy makes it appropriate for clinical applications where both precision and time are of the paramount importance.

Data Inputs

Chest X-Ray Datasets: The study takes use of a big collection of chest X-ray images, which cover a wide range of lung disorders, ranging from normal to varied pathologies. The images cover a wide variety of lung ailments. As a result of the heterogeneity that exists between approaches, the robustness of the segmentation process is guaranteed across a wide range of scenarios.

Preprocessing of Image: In order to execute pretreatment processing on each and every X-ray image, the Gaussian filter with normalized gradient is applied. This filter is used to do image pretreatment. This phase must be finished in order to increase the delineation of lung borders and to get the image suitable for the subsequent segmentation process.

Process of segmentation: The images are preprocessed and thereafter the snake or active contour segmentation is applied. This is to initiate the segmentation process. In order to reduce the anticipated amount of energy functions by the model, this is accomplished through several iterations using the control points. As a result, the snake may exactly match the edges of the lungs.

Implementation

The method that is being discussed is a two-step process that combines the segmentation of the lung field in chest radiographs employing a snake or active contour along with a Gaussian filter with a normalized gradient. This approach is provided with the intention of segmenting the lung fields. This method is helpful in providing a medical community basis for lung field segmentation. Recognizing the lung boundaries is a very important stage in the subsequent process of medical analysis and diagnosis. This technique aims to increase the accuracy and efficiency of recognizing the lung boundaries, which is a very critical stage in the process.

While processing the initial stage of the implementation process for the chest radiograph, the Normalized Gradient Gaussian Filter is applied. At the same time, the stage has importance since it leads to the enhancement of the structure of lung boundaries. As such, this stage is given utmost importance, meaning that it calls attention to the particular lung regions that are exceptional. This stage has been done in such a way that filtering was meant to highlight gradient information while minimizing noise at the same time. This was done without having any adverse effect on the rest of the process. Both functions are combined with each other to achieve this. Because this assures that the succeeding stages will not suffer from additional picture data that does not contribute to the segmentation process, this noise reduction has, therefore, become very essential to enable the realization of a successful segmentation process. Shortly following the application of the filter, the picture that has been processed is subjected to the process of snake or active contour segmentation. This occurs shortly after the filter has been applied. During this kind of process, a deformable model that is also referred to as an active contour or "snake" is utilized. In order to generate the lungs ideal shape, this model is utilized. The fundamental goal of this model is to reduce the amount of energy that is necessary to confirm the contour in order to complete the process of achieving the ideal shape of the lungs. This constitutes the primary objective of the model. Within this framework, the snake model is applied in order to clearly highlight the structure and outlines of the various components of the lungs. This is done in order to achieve the level of precision that is required.

The real model of the snake is comprised of many control nodes or points that cooperate to create a curve. All these nodes and points are joined together, forming the curve. Then, such nodes and points were joined to one another in a complex network. So, using the nodes, one can easily get the desired shape for the lung borders when doing surgery and thus can be carried out. This has the potential to be done. Several stresses are applied to the snake model so as to make it move and achieve the desired shape that is associated with the lung. For this, those forces are the internal energy forces that guarantee that the curve keeps smooth and flexible. Under the category of forces that are responsible for maintaining the curve, both of them constitute the category. Their interaction is directly responsible for the snake model being able to precisely monitor the limits of the lungs.

The snake model must be able to withstand both external and internal pressures it will face during the iterative process if it is to be successful. The form of the snake will thus be modified in order to be able to attain a good form that closely resembles the borders of the lungs, at the same time minimizing the amount of energy that is necessary. This form is the best for that reason. Since it uses mathematical polynomials to explain the geometric arrangements, the snake model is thus in a position to provide a realistic portrayal of the complex structures of the lungs. This is because the model uses polynomial math. Though this, in no way, means the snake model is flawless, and this will be possible if the spline representation is required. This, therefore, makes it a distinct possibility. The representation of splines is what makes this possible.

There are three different forms of energy present in the all-encompassing energy of the snake model: image energy, which is the energy originating internally, and energy resulting from external influences. The exterior energy is responsible for pushing the snake towards the image margins and regions of substantial interest. However, as far as internal energy is concerned, it is responsible for ensuring smooth adherence of the snake to the borders of the lung, whereas the external energy is responsible for moving the snake. With the help of the image energy term, made up of information derived from the image itself, the snake is able to align correctly with lung areas without encountering any problems.

In the field of medical imaging, in the event that it proved that the snake model is very useful in the process of lung field segmentation, this is through the research. This is to say, there has been a discovery that pertains to it. It can apply in many areas, including vascular area segmentation, cell image segmentation, optic disc and cup detection for glaucoma, among other situations where accurate structure delineation is critical for diagnostic and research purposes in disease conditions.

Since the application here is for the extraction of a left lung from the chest image, a snake model will be applied for this particular purpose. The left lung has then to be subjected for further processing and analysis after it has been encased within a contour or shape. This follows the next stage in the process. By means of being a snake model, it would be possible to segment specific lung regions in a suitable manner. This is therefore possible. As a result of this, it is now possible to extract features for automating the analysis of anomalies.

In fact, one of the most used models is the snake model, which, however, can be influenced by background noise, and its ability to detect those items that are intricate can be an issue. This should not be underestimated. In order to overcome these issues and to improve the accuracy of segmentation, which are quite difficult in challenging working conditions, more complex versions of the snake model have been developed. Both have been successfully accomplished. Because of the more complex approaches and algorithms being used in the most recent versions, the segmentation process has been improved to an even greater level.

Lung field segmentation using the Gaussian filter with normalized gradient and snake or active contour segmentation gives a reliable approach for border recognition in chest radiographs. This technique is applicable in conditions where the lungs are not clear. In the view of segmenting the lung field, this technique uses snake or active contour segmentation. This method can be concluded to have a valid strategy that does not have any shortcomings. This makes use of the enhanced picture information given by the filter, together with the adaptive nature of the snake model, to precisely capture the complexities and curves that exist in the lung. This has been done to ensure that the results are as accurate as possible. This availability of this level of extensive segmentation enables medical practitioners to remove secure lung parts for the purpose of doing more studies and establishing accurate diagnoses. This is made possible because the segmentation is provided at this level. As a result of this, the diagnosis and evaluation of problems in the pulmonary system are much enhanced, which results in a major improvement.

Result and Discussion

There is much potential in improving the delineation and analysis of lung sections as this has been achieved as the Gaussian filter with normalized gradient and Snake or active contour segmentation approach were used for the purpose of lung field segmentation in chest radiography. This advanced method of segmentation opens up various study and evaluation possibilities in anomalies within the pulmonary system in that it effectively identifies and outlines areas of interest in the lungs. This method also affords an opportunity to identify and outline areas of interest.

As illustrated in Figure 1, the successful segmentation process of an abnormal lung picture utilized both the active contour model (ACM) and the structured edge detector (SED) snake or active contour segmentations. This image shows how the segmentation approach is able to successfully segment the abnormal lung part while also clearly outlining the borders of the lung, which include the inner and the outer areas.

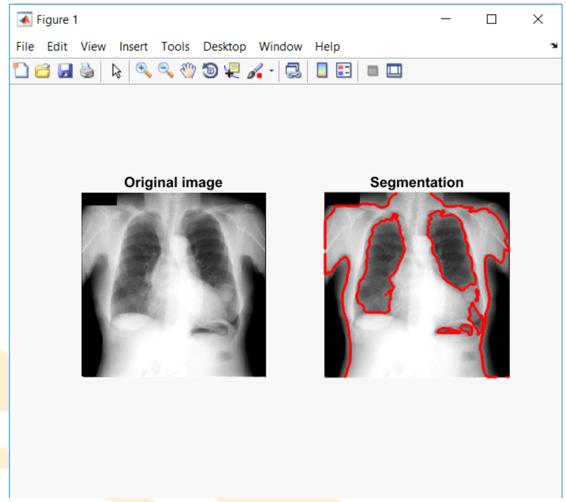

Figure 1. Lung Field Segmentation result output

Further, Figure 2 depicts the last lung segmented output. This image indicates that the segmentation is doing its job properly, making the lung field highly clear and defined.

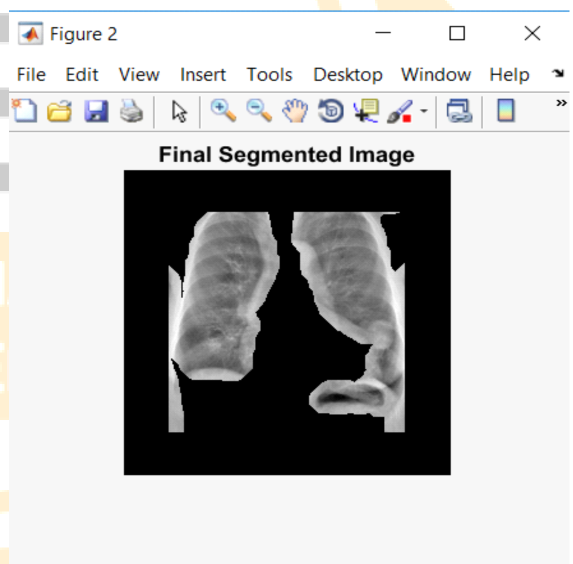

Figure 2. Segmentation Output

Figure 3 illustrates the segmented mask as well as the processing time, a visual representation that highlights the effectiveness of the segmentation process in comparison to structure edge detector universal contour model (SEDUCM). This chart highlights the decreased processing time, which is an essential component in clinical situations where time efficiency is of the utmost importance.

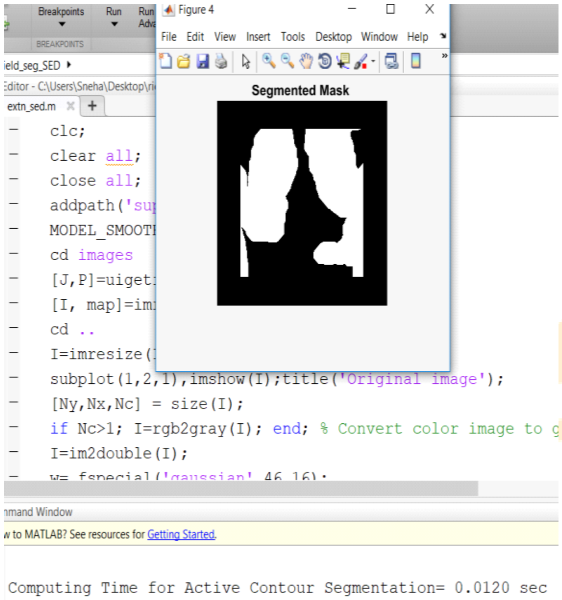

Figure 3. Processing time and segmented mask

Accuracy of Segmentation: The findings indicate a high level of accuracy in the delineation of lung fields, with a distinct segmentation of lung outlines and interior components. Through the use of this approach, lung tissues can be efficiently differentiated from the anatomical elements that surround them. Table 1 shows comparative results of the proposed approach with the existing one and reveals that the proposed approach gives better results in comparison the existing one. The existing method referred to as SEDUCM utilizes a Gaussian Filter in conjunction with a Snake Model for lung segmentation. Although this method provides moderate accuracy with some misclassifications, it is less robust against noise and shows good adaptability to variations in lung shapes, but with less flexibility to extreme variations. The processing time is relatively longer, approximately 1.8 seconds per image, making it less ideal for rapid diagnostics. While generally effective in detecting anomalies, it may overlook finer details, thus offering adequate utility in standard clinical diagnostics but with limitations in detailed lung boundary delineation.

Table 1: Comparison of Results

Metric	**SEDUCM Method**	**Gaussian Filter with Snake Model**
Segmentation Accuracy	Moderate accuracy with some misclassifications	High accuracy due to precise edge detection
Robustness to Noise	Less robust, susceptible to noise	Highly robust, effectively minimizes noise effects
Adaptability to Variations in Lung Shapes	Good, but less flexible to extreme variations	Excellent adaptability to anatomical variations
Processing Time	Longer, approximately 1.8 seconds per image	Significantly reduced, approximately 0.2 seconds per image
Utility in Clinical Diagnostics	Adequate for standard diagnostic purposes but less detailed	Enhanced utility due to detailed lung boundary delineation
Effectiveness in Anomaly Detection	Generally effective, but may miss finer details	Highly effective in identifying subtle anomalies

The combined approach demonstrates a considerable reduction in processing time when compared to previous method, without losing accuracy. This is a significant improvement in processing efficiency. In clinical settings, this efficiency is absolutely necessary for the speedy diagnostic and treatment planning that takes place. The JSRT dataset refers to the "Japanese Society of Radiological Technology" dataset. It's a widely used benchmark in medical imaging, specifically for the evaluation of computer-aided detection (CAD) systems in chest radiographs. This dataset includes chest X-ray images that are used to develop, test, and compare algorithms for lung field segmentation, nodule detection, and other diagnostic tasks. The high-quality, standardized images in the JSRT dataset provide a valuable resource for researchers to advance image analysis techniques in the field of radiology.

The approach shows both adaptability and robustness in that it can serve to accommodate a broad spectrum of lung diseases and be resilient against common image quality problems, such as noise and low contrast.

Conclusion:

In the present work, lung field segmentation is carried out using snake or active contour segmentation Approach with normalized gradient Gaussian filter. Additionally, the presented approach is compared with SEDUCM and found more appropriate. The present work contains an immeasurable contribution in the analysis of chest radiography. The work adds to the continued development of medical imaging and patient care in the field of pulmonologist through using sophisticated image processing techniques and incorporating them into a coherent and efficient workflow.

In summary, lung field segmentation in chest radiography is the subject of Gaussian filtering with normalized gradient and active contour segmentation or Snake approach. This technique advances medical imaging and diagnosis and time taken for the process of our project 0.01 only. The combination has proven to be very effective in defining the boundaries of the lung and locating areas of interest within the lung field, both of which are necessary for accurate diagnosis and effective patient care.

References

[1] W Yang, Y Liu, L Lin, Z Yun and Z Lu et al., ”Lung Field Segmentation in Chest Radiographs from Boundary Maps by a Structured Edge Detector,” in IEEE 2017.

[2] M. Yahyatabar, P. Jouvet and F. Cheriet, "Dense-Unet: a light model for lung fields segmentation in Chest X-Ray images," 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Montreal, QC, Canada, 2020, pp. 1242-1245, doi: 10.1109/EMBC44109.2020.9176033.

[3] S. Agarwala, D. Nandi, A. Kumar, A. K. Dhara, S. B. T. A. Sadhu and A. K. Bhadra, “Automated segmentation of lung field in HRCT images using active shape model”TENCON 2017 - 2017 IEEE Region 10 Conference, Penang, Malaysia, 2017, pp. 2516-2520, doi: 10.1109/TENCON.2017.8228285.

[4] G. Singadkar, S. Talbar and S. Talbar, "Automatic lung field segmentation using feature extraction and unsupervised learning," 2017 International Conference on Innovations in Electronics, Signal Processing and Communication (IESC), Shillong, India, 2017, pp. 28-32, doi: 10.1109/IESPC.2017.8071859.

[5] Z. Kunpeng and S. Xin, "Automatic lung field segmentation based on the U-net deep neural network," 2019 14th IEEE International Conference on Electronic Measurement & Instruments (ICEMI), Changsha, China, 2019, pp. 1670-1676, doi: 10.1109/ICEMI46757.2019.9101832.

[6] M. N. Saad, M. F. M. Mohsin, H. A. Hamid and Z. Muda, "Lung Area Segmentation on Chest X-Ray Based on Texture Image Feature," 2021 11th IEEE International Conference on Control System, Computing and Engineering (ICCSCE), Penang, Malaysia, 2021, pp. 92-96, doi: 10.1109/ICCSCE52189.2021.9530963.

[7] J. Hu and P. Li, "An Automatic Lung Field Segmentation Algorithm Based on Improved Snake Model in X-ray Chest Radiograph," 2021 33rd Chinese Control and Decision Conference (CCDC), Kunming, China, 2021, pp. 1845-1851, doi: 10.1109/CCDC52312.2021.9602464.

[8] A. Mansoor et al., "A Generic Approach to Lung Field Segmentation From Chest Radiographs Using Deep Space and Shape Learning," in IEEE Transactions on Biomedical Engineering, vol. 67, no. 4, pp. 1206-1220, April 2020, doi: 10.1109/TBME.2019.2933508.

[9] J. K, N. P. Deendayal, G. K. Dhindsa, A. Nagrani and V. Bali, "CT Intensity Segmentation of Lungs," 2022 2nd International Conference on Intelligent Technologies (CONIT), Hubli, India, 2022, pp. 1-6, doi: 10.1109/CONIT55038.2022.9847825.

[10] Y. Li, Z. Jiang, K. Zhang, W. Shi, F. He and J. Liu, "Dense-U-Net: A densely connected CNN for lung fields segmentation," 2020 International Conference on Virtual Reality and Visualization (ICVRV), Recife, Brazil, 2020, pp. 128-131, doi: 10.1109/ICVRV51359.2020.00035.

[11] P. Pattrapisetwong and W. Chiracharit, "Automatic lung segmentation in chest radiographs using shadow filter and multilevel thresholding," 2016 International Computer Science and Engineering Conference (ICSEC), Chiang Mai, Thailand, 2016, pp. 1-6, doi: 10.1109/ICSEC.2016.7859887.

[12] R. Arora, I. Saini and N. Sood, "Modified UNet++ Model: A Deep Model for Automatic Segmentation of Lungs from Chest X-ray Images," 2021 2nd International Conference on Secure Cyber Computing and Communications (ICSCCC), Jalandhar, India, 2021, pp. 166-169, doi: 10.1109/ICSCCC51823.2021.9478101.

[13] J. Wang, Z. Li, R. Jiang and Z. Xie, "Instance Segmentation of Anatomical Structures in Chest

Radiographs," 2019 IEEE 32nd International Symposium on Computer-Based Medical Systems (CBMS), Cordoba, Spain, 2019, pp. 441-446, doi: 10.1109/CBMS.2019.00092.

[14] M. S. Alam, D. Wang and A. Sowmya, "Image data augmentation for improving performance of deep learning-based model in pathological lung segmentation," 2021 Digital Image Computing: Techniques and Applications (DICTA), Gold Coast, Australia, 2021, pp. 1-5, doi: 10.1109/DICTA52665.2021.9647209.

[15] P. B. Chanda and S. K. Sarkar, "Effective And Reliable Lung Segmentation Of Chest Images With Medical Image Processing And Machine Learning Approaches," 2020 IEEE International Conference on Advent Trends in Multidisciplinary Research and Innovation (ICATMRI), Buldhana, India, 2020, pp. 1-6, doi: 10.1109/ICATMRI51801.2020.9398450.

[16] A Sharafeldeen; A Alksas, M Ghazal, M Yaghi, A Khelifi, A Mahmoud, Sl Contractor, E van Bogaert, "Accurate Segmentation for Pathological Lung Based on Integration of 3D Appearance and Surface Models, "2023 IEEE International Conference on Image Processing (ICIP), Kuala Lumpur, Malaysia, 2023, pp. 3130-3134, doi: 10.1109/ICIP49359.2023.10222525.

[17] J. Hou, C. Yan, R. Li, Q. Huang, X. Fan and F. Lin, "Lung Nodule Segmentation Algorithm With SMR-UNet," in IEEE Access, vol. 11, pp. 34319-34331,2023,doi: 10.1109/ACCESS.2023.3264789.

[18] M. Divya and S. Sathya, "MedNet: A Segmentation Algorithm for Effective Lung cancer Diagnosis," *2023* 5th International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India, 2023, pp. 1633-1640, doi: 10.1109/ICSSIT55814.2023.10061117.