ORIGINAL ARTICLE

CT-Based Auto Lung Damage Assessment COVID-19

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Abstract

Purpose: Monitoring disease development or viruses that invade our bodies, such as Coronavirus Disease of 2019 (COVID-19), can be effectively carried out using Computed Tomography (CT) imaging tools. However, manual assessment of CT images by consultants is often insufficient for determining the extent of lung damage in COVID-19 patients. Automated evaluation of lung damage addresses this limitation by optimizing healthcare resource utilization. It reduces the workload on radiologists, allowing them to concentrate on more complex cases. Additionally, it ensures accurate and consistent assessments of lung damage, minimizing variability and the potential for human error inherent in manual evaluations.

Materials and Methods: In this study, a new approach was presented for improving CT images of the lung and specifying further lesions. This will help calculate the extent of damage without human intervention. The structure of the proposed technique draws upon four phases (data collection, improvement, segmentation and extraction lung damage region and evaluation). Firstly, 100 patients were recruited between September 29 2020 and July 10, 2022, of whom tested positive for COVID-19 and CT images were collected, then composite technique is implemented to extract the percentage of lung damage of COVID-19 patients.

Results: The study results demonstrated an efficient method for quickly and practically calculating the percentage of lung damage. There is a clear convergence between manual evaluation, done by radiologists, and automatic evaluation using the proposed method, suggesting its potential as an alternative in the absence of a specialist doctor. The differences in the arithmetic mean between the proposed technique and the radiologists' evaluations were 3.5%, 10%, 18%, and 0.98% for radiologists 1, 2, 3, and 4, respectively. Additionally, the findings indicated that individuals aged 20-60 years are the most affected by COVID-19.

Conclusion: This method serves as a potent tool for swiftly and practically assessing the percentage of lung damage caused by COVID-19. By eliminating the need for human intervention, it enables the evaluation of lung damage autonomously. This feature makes it particularly valuable in telemedicine applications and emergency situations where specialist medical expertise may not be readily available.

Keywords: Coronavirus Disease of 2019; Image Analysis; Lung Damage Assessment; Radiologist Examination.

DOI:

1. Introduction

Coronavirus Disease of 2019 (COVID19) is one of the emerging and mutating viruses that appeared at the end of 2019. As this virus caused economic and social damage that greatly affected the general performance of the people as many died. Symptoms of this virus include headache, throat burning, diarrhea [1, 2]. The fierce crisis of the corona virus affected the general performance of the world, as the rapid virus spread and claimed many people around the world and still is. Therefore, we need an automatic technique that supports us in the early detection and treatment to prevent infection and reduce its spread.

Computed Tomography (CT) technology can be used as a way to monitor what is happening in the lungs as a result of the virulence of this virus. It is possible to depend on PCR test to identify COVID-19 patient, but sometimes patient of COVID-19 has symptoms and its PCR test is negative [3]. Therefore, CT scan could be a supporting tool in making a decision about the effect of this virus on a patient's lung. However, the usual way for a specialist doctor to determine lung damage is to specialist doctor to determine lung damage is to divide the right lobe and the left lobe of the lung into sections, and then determine the level of damage in each section and give the total percentage of lung damage [4 ,5], see Figure 1.

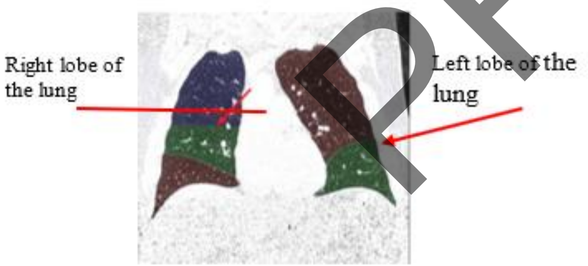

Figure 1. Illustrate coronal view of right and left lobes of the lung and its sections, this figure adopted from [4]

This method is error prone and differs from one doctor to another because it depends on the doctor's vision and experience. Recruiting digital image processing techniques for the automated analysis of CT scans is a strategy to determine the level of lung damage without human intervention. Furthermore, it is possible to help consultants obtain and reinforce the correct diagnosis. The tools of the digital image processing include image enhancement, segmentation and analysis. Table 1 which illustrated below, presents a set of researchers who interested and applied a new method for enhancement, segmentation and detection COVID-19 patient.

From previous studies, we can understand the topic more accurately, as looking at previous studies allows first to filter out useless ideas and secondly to show the most important ideas that should be focused on.

Deep learning neural networks show that the ability to distinguish images of the mare is higher and faster than the specialist's diagnosis. However, deep learning is data hungry and it is expensive to time. Through performing fuzzy image techniques needs experience and knowledge to analyze problem components and build fuzzy rules. Furthermore, pre-processing step such as image enhancement is necessary step to obtain desired results. In this paper, we proposed a novel technique to evaluate lung damage spontaneously. This technique consists of four steps data collection, image enhancement, image segmentation and extraction lung damage region and evaluation the percentage of lung damage.

The remainder of the paper cab be summarized as follows: details of the methodology incorporating the automated method are in Section 2. The results and discussions are described in Section 3 and finally the conclusions and future work are outlined in Section 4.

2. Materials and Methods

Lung damage evaluation of the COVID-19 patients have the potential to mirror the severity of the disease locally within the respiratory system. Corona virus infection was initially discovered, depending on the nature of the patient's symptoms and the speed of the disease's spread, and this is confirmed by laboratory examination and computed tomography. Sometimes the patient has signs of disease, but laboratory analysis does not confirm this. Therefore, we need to see and monitor what is happening to the respiratory system through on-site imaging using a CT scan. Radiologists depend on determining the percentage of damage to the lung by assigning the damage to each lobe of the lung and then dividing each lobe according to its size into sections and then summing the percentage and determining the total percentage of damage. This work requires time and depends entirely on the ability and experience of the specialist doctor in diagnosis. In this paper we set out automated technique to provide a

Table 1. presents a set of researchers who analysis CT image of COVID-19 patient

Year of publication	Authors	Motivation	Idea	Limitations
2020	He, X. *et al.* [6] Harmon, S. A. *et al* [7] Zheng, C. *et al* [8] Li, L. *et al* [9]	Sometimes PCR test does not tell us about COVID-19, despite the presence of symptoms of the virus CT scan is more sensitivity than other test in detecting COVID-19 associated pneumonia or not.	CT scan is more sensitivity than other test in detecting COVID-19. Therefore, in the first article, 1337 CT images were involved in the technique, while the second one used 1280 CT images. The main idea in both articles concerned about classification of COVID-19 associated pneumonia or not, techniques of the two articles are performed using deep learning technique	It is better to do some pre-processing steps such as enhancement of the CT images (contrast enhancement) before applying deep learning technique because image data suffers from noise.
2020	Gunraj, H. *et al.* [10]	CT images is a convenient choice for illustration the impact of COVID-19 on the lung's patient.	Diagnosis and Detection of COVID-19 patient. 1489 CT image were involved in this work.	It is better to do some pre-processing steps such as enhance CT image (contrast enhancement) before applying deep learning technique because the data is noisy.
2021	Kumar, S. N. *et al.* [11]	The traditional segmentation technique is sensitive to noise	Using Fast Fuzzy C means for image CT image segmentation of COVID-19 patients' lesions	This work needs pre-processing step such as image enhancement.
2022	Alzahrani, A. *et al.* [12]	The same motivation of previous article.	Enhancement of CT image contrast of COVID-19 patients based on fuzzy membership function. In the first article, 254 CT image were involved in this work.	Fuzzy membership function is inherent human thinking, so it requires more knowledge and experiences.
2022	Jabbar, S. I. *et al.* [13]	The same motivation of previous article.	Enhancement of CT image contrast of COVID-19 patients based on modified unsharp masking technique. 100 patients were recruited to collect CT images of COVID-19 patients.	Modified unsharp masking focused on enhancing CT images contrast, but it was applied on limited set of data (30 image samples)
2023	Tache, I.A *et al* [14]	The same motivation of previous article.	Trained deep learning (CNN) to detect lung damages.	Convolutional neural network (CNN) is hungry to data. It means that need more data to get accurate evaluations
2024	Proposed technique	Preparing an integrated plan to reach the goal, which is to calculate the amount of lung damage due to the Corona virus	It will cover Enhancement, segmentation and lung damage evaluation steps and 100 patients will be recruited in this work.	The images were collected from hospitals individually and were not taken from a website, so as a future work we need to expand a set of data.

quick, practical and standard solution, which is based entirely on the analysis of the changed chromaticity characteristics due to the virus attack on the lung. This technique consists of several main parts, the first of which is the collection of data, then the implementation of the technique, and finally the analysis and comparison of the results with the assessment of radiologists.

2.1. Data Collection

100 patients were recruited between September 29 2020 and 10 July, 2022, of whom tested positive for COVID-19, CT images of these patients were collected from Al-Ghadeer Clinic for X-ray, Ultrasound and Helical CT scan, Babylon, which approved for giving us Ct images with the serial number (410227G). CT images of COVID-19 patients illustrate different levels of lung damage as grey scale regions. The ages of COVID-19 patients between (18-80) year with signed written consent letters and CT images were collected randomly for a number of patients infected with Covid 19.

2.2. Proposed Technique

The initial step in this technique involves image enhancement using an anisotropic diffusion filter, as referenced in [15-17]. The primary objective of employing this filter is to mitigate image noise, thereby minimizing the potential for erroneous diagnosis and evaluation of lung damage. Specifically, the filter preserves essential features such as edges, lines, and other significant details that convey image content, while effectively reducing noise in CT images.

The utilization of the anisotropic diffusion filter serves to prepare the images for subsequent analysis, particularly in the separation of distinct image components representing healthy and damaged lung regions. This segmentation process is crucial for accurately determining the percentage of damaged areas relative to normal lung regions. By effectively isolating these regions, the technique facilitates precise evaluation and characterization of lung damage, thus enabling more informed medical decision-making.

In this work, Otsu method was recruited to perform this step. The Otsu method is a widely recognized technique for distinguishing various components within an image, such as the object of interest and the background. It operates by maximizing the variance between different pixel classes, thereby identifying an optimal threshold that effectively segments the image into distinct regions. This method is particularly useful in medical imaging applications [18, 19]. However, images processed using this method still require additional morphological processing to accurately determine the percentage of lung damage. Morphological image processing [20-22] constitutes as a powerful set of tools for extracting features of medical images. For this reason, it has been invested in preparing the image to the final step (evaluation of percentage of lung damage). Person correlation coefficient [23-25] was used to detect the convergence between manual and automated evaluations. Figure 2 below illustrates the pipeline this technique.

The first step of this technique is image enhancement using an anisotropic diffusion filter [15-17]. The primary aim of using anisotropic diffusion filter has therefore been to reduce the image noises and risks associated with wrong diagnosis and evaluation of lung damage. In particular, this will keep edges, lines and other significant details which describes image contents. Anisotropic diffusion filter was involved to reduce noise of CT images and prepared it for the next step, which is the separation of image components including healthy and damaged lung regions. Separating the different areas of the image (the areas of the healthy lung and the affected lung) is an essential step to deter*mine the percentage of the damaged regions to the normal lung regions. In this work, Otsu method [18, 19] was recruited to perform this step. However, the processed images still needed to some morphological processing to extract the accurate percentage of lunge damage. Morphological image processing [20-22] constitutes as a powerful set of tools for extracting features of medical images. For this reason, it has been invested in preparing the image to the final step (evaluation of percentage of lung damage). Person correlation coefficient [23-25] was used to detect the convergence between manual and automated evaluations. Figure 2 below illustrates the pipeline this technique.

The performance of work in this paper was assessed quantitively using statistical tools such as mean, standard deviation, and Pearson correlation coefficient. The mean helps gauge the average lung lesion percentage, while standard deviation indicates the variation or dispersion in these percentages among patients, potentially highlighting differences across age groups. The Pearson correlation coefficient is used

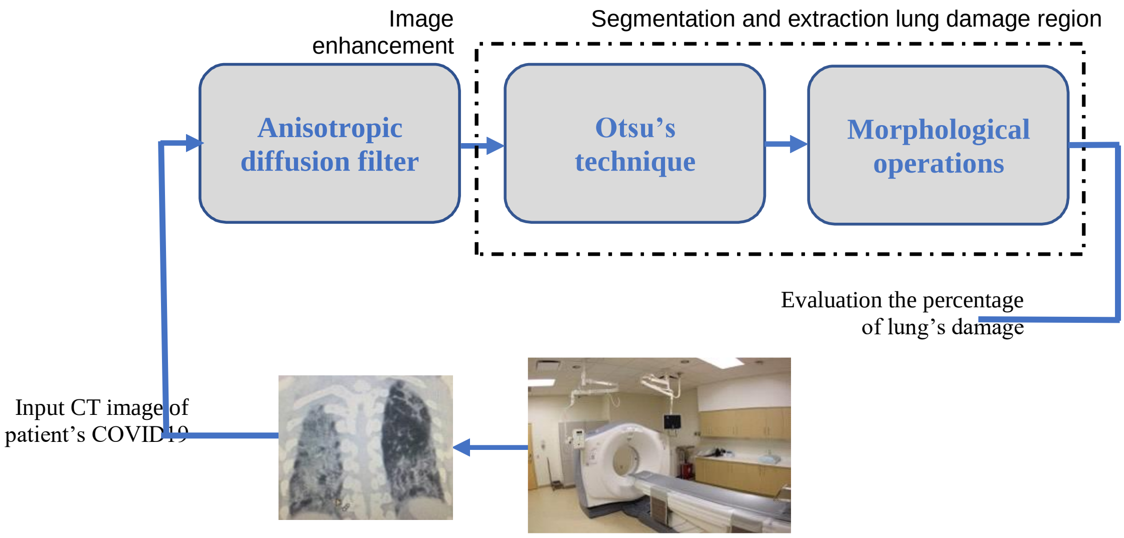

Figure 2. Illustrates the pipeline of proposed technique

to compare the effectiveness of different assessment methods or to measure the similarity between automated results and those provided by radiologists.

3. Results

Subjective evaluations of CT scan images are commonly employed in assessing lung lesions due to their critical role in diagnosis, albeit this approach typically demands significant time from medical professionals. This manual assessment entails dividing the lung into four sections, evaluating the extent of corruption in each segment, and subsequently aggregating the findings to derive a final assessment. However, this process is time-intensive and heavily reliant on the expertise of radiologists.

To address these challenges, a self-assessment technique was proposed in this study to automatically determine the percentage of lung damage inflicted by the coronavirus. This method solely relies on tracking changes in the color values of tomographic images. By employing this approach, it becomes feasible to ascertain the extent of damage automatically, especially in scenarios where specialized medical personnel are unavailable.

Four radiologists assessed the CT images of COVID-19 patients. Two conducted their evaluations during the data collection phase, while the other two assessed the severity of the lung images after the complete set of images had been collected Figure 3 represents some examples of CT scan images of lungs from COVID-19 patients at different levels and ages. This figure demonstrates the ability to automatically determine the percentage of lung damage. Light gray areas within the lung images indicate the damage caused by the virus. Furthermore, highlights the advantage of the automated method in speed and accuracy compared to manual calculations.

On the other hand, Figure (4 a-b-c-d) illustrates the divergence and convergence in the opinions of radiologists concerning the extent of lung damage caused by COVID19, as well as the effectiveness of the proposed method for different age groups.

The quantitative assessment method can be recruited to assess the convergence and divergence between a proposed method and radiologists' assessments of lung lesions. This assessment uses statistical tools such as mean, standard deviation, and Pearson correlation coefficient. This approach aims to provide a robust statistical framework for evaluating diagnostic methods in lung damage assessment. Table 2 demonstrates a convergence between our proposed technique and the radiologists' assessments

4. Discussion

A study collected 100 CT scan samples of lung images from patients across various age groups, ranging from their twenties to their eighties. These CT scan images were initially evaluated directly by two radiologists. Recent evaluations by other radiologists have corroborated the initial findings. In this work, a new

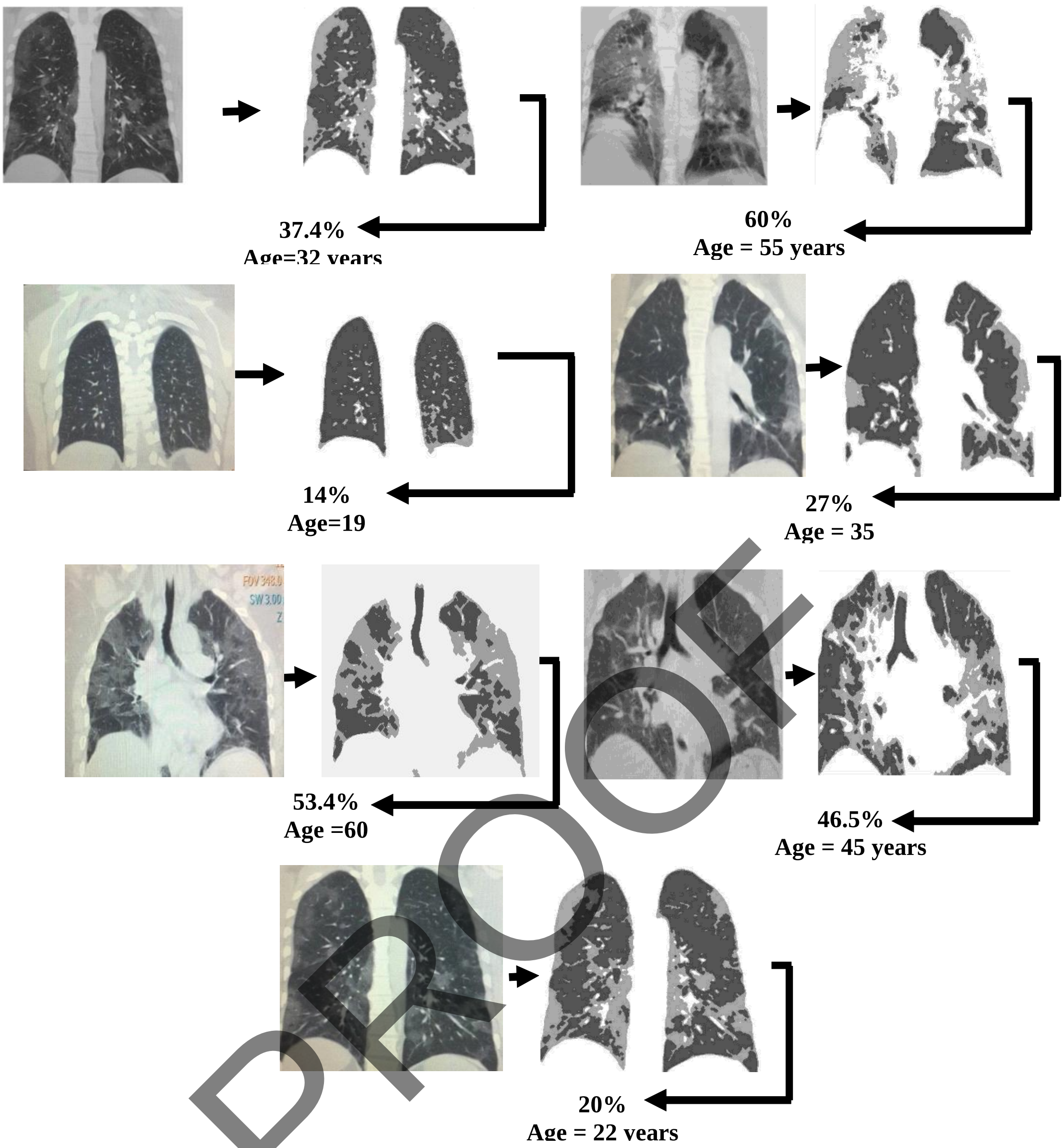

Figure 3. The percentage of lung damage from COVID 19 patients is illustrated by the proposed technique

technique was proposed that consist of composite image possessing tools (enhancement, segmentation and features extraction). This technique was applied to these image samples to get an automated evaluation of the percentages of lung damage of COVID 19 patients, see the results in the Figure 3. The results illustrate the percentages of lung damage observed for each age group were as follows: twenties: 10% to 45%, forties: 10% to 60%, sixties: 5% to 80%, eighties: 10% to 60% as presented in the Figures 4. The data reveals a variation in the extent of lung damage across different age groups. Notably, the sixties age group shows a vast range of lung damage. This suggests a significant variation in the impact of lung conditions within this group. However, given that the number of samples is 100 samples, expanding the dataset is necessary to derive more precise conclusions. Statistical metrics evaluation in Table 2, collectively validates the proposed automated methodfor assessing lung damage in COVID-19 comparing it with traditional radiological methods, and quantifying the similarity through statistical correlation. Specifically, the difference in the arithmetic means between the proposed technique and four radiologist assessments respectively 3.5%, 10%, 18% and 0.98%. Additionally, the other statistical metrics values show differences but are very close between the proposed method and the radiologists' assessments.

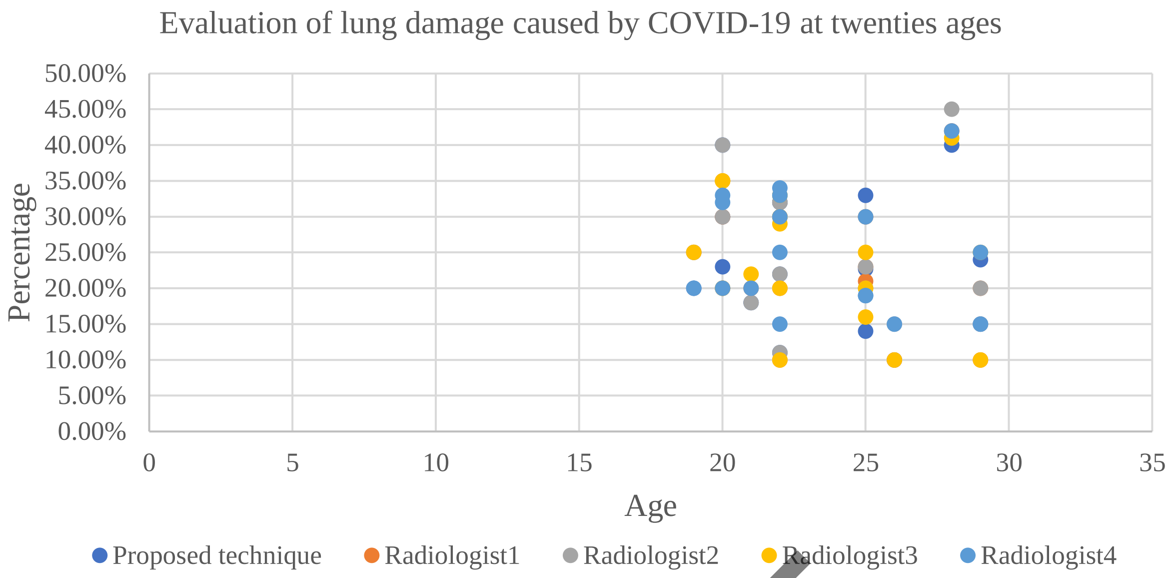

Figure 4a. Illustrates different percrntage of lung damage of twenties ages bassed on data collected, this data was evaluated by proposed and radiologist (1,2,3,4) assessment

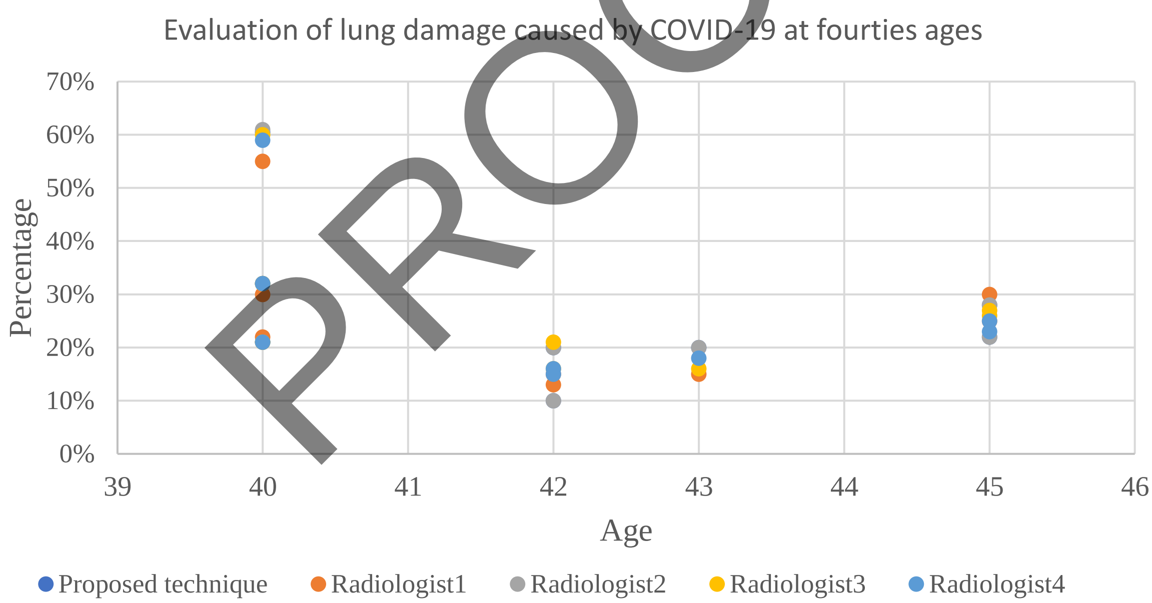

Figure 4b. Illustrates different percrntage of lung damage of fourties ages bassed on data collected, this data was evaluated by proposed and radiologist (1,2,3,4) assessment

5. Conclusion

The research introduces a straightforward and efficient approach for evaluating lung damage, offering potential applicability in scenarios where medical professionals are unavailable. This automated method relies on analyzing the characteristics of Computed Tomography (CT) images, enabling rapid assessment without the need for a doctor's intervention.

The study emphasizes the significance of sample size in ensuring the robustness of results, highlighting that larger sample sizes contribute to more reliable outcomes. Therefore, as a future direction, the researchers recommend expanding the sample size to include a

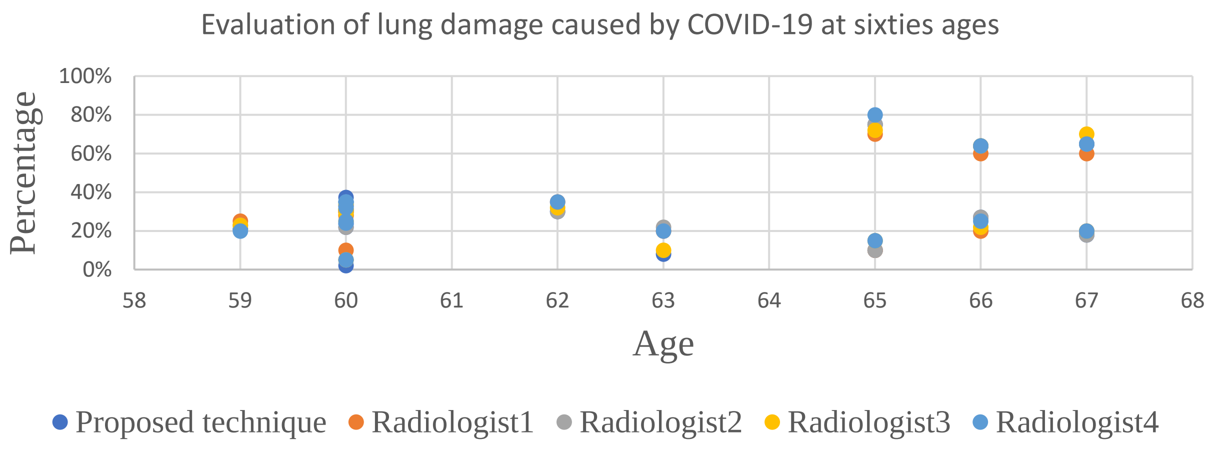

Figure 4c. Illustrates different percrntage of lung damage of sixties ages bassed on data collected, this data was evaluated by proposed and radiologist (1,2,3,4) assessment

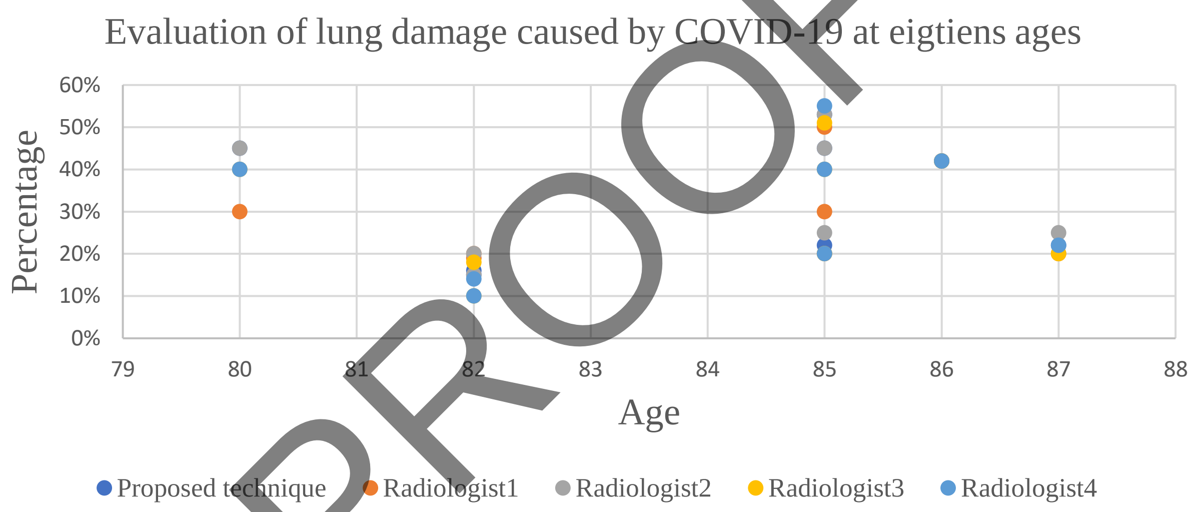

Figure 4d. Illustrates different percrntage of lung damage of eighties ages bassed on data collected, this data was evaluated by proposed and radiologist (1,2,3,4) assessment

Table 2. convergence between our proposed technique and the radiologists' assessments

Methods	Mean	Standard deviation	Person correlation coefficient
Proposed	30.8299	15.42	1
Radiologist1	29.7400	13.77	0.93
Radiologist2	27.5%	13.68	0.96
Radiologis3	26%	14.4	0.91
Radiologis4	31%	15.42	0.98

broader range of cases. This expansion could enhance the generalizability and validity of the findings.

Furthermore, the researchers propose integrating the developed method into updated tomography devices. This integration would facilitate expedited determination of damage levels, particularly in situations where specialist medical attention is unavailable or in emergency scenarios where prompt action is imperative to prevent virus progression or transmission.

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