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An Automated Deep Learning-Based Software for Total Lung Volume Calculation and Lung 3D Model Reconstruction

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Abstract

In this paper, we propose an automated deep learning-based software, especially for reconstructing 3D lung images and estimating Total Lung Volume (TLV). The system is mainly designed for Vietnamese users with Vietnamese as the default language. The purpose of our study is to build an automated system based on deep learning and machine-learning models to measure TLV and construct a 3D prototype of the lung. The training data is collected from The Cancer Imaging Archive (TCIA) dataset, provided by the 2017 Lung CT Segmentation Challenge for training and testing the proposed model. Our proposed system utilizes a modified Bi-directional Convolutional (ConvLSTM) U-Net (BCDU-Net) neural network. We use the lung segmentation results as the data to build 3D lung image and calculate the lung volume. We test the reliability of the software with real dataset collected from Bach Mai hospital. The overall results have shown that accuracy against actual data from commercial products is approximately 99% when using our model to calculate the TLV.

Keywords: Deep learning, lung CT image, total lung volume, 3D reconstruction.

1. Introduction

According to World Health Organization (WHO) [1], with approximately 1.8 million deaths annually, lung cancer remains the 2nd most prevalent type of cancer in the world. An estimated amount of 228,820 new lung cancer cases [2] and 135,729 death cases are annually diagnosed in the United States.

Computed tomography (CT) imaging is currently one of the most efficient and widely used medical screening methods for a broad spectrum of diseases, including lung diseases. In the United States, an estimation of 80 million CT scans are annually performed [3], which play an essential role in detecting, diagnosing, treating thoracic diseases, and monitoring the treatments' effectiveness. They have also proven to increase treatment options by eliminating the need for conventional invasive and risky procedures. Moreover, researchers have recently begun to build automatic artificial intelligence (AI) systems based on CT scans that can detect a variety of ventilatory defects and collect quantitative clinical measurements. AI systems show potential applications in the routine assessment of numerous biomarkers [4] related to pulmonary diseases, or osteoporosis. It would be a huge milestone in the field of routine quantitative radiology examination.

Total Lung Volume (TLV) [5] is the most effective approach for assessing the severity, progression, and response to treatment in restrictive lung diseases. Accurate measurement of lung volumes is essential in detecting ventilatory defects and plays a key role in aiding medical specialists in diagnosing early signs of lung diseases and subsequently configuring a suitable treatment for the patients. It is the key measure in quantifying lung parenchyma and lung lesions presenting different appearances. In this paper, we concentrate on the application of machine learning and the CNN model in calculating the total volume and reconstructing the 3D prototype of lung segmentation. TLV could detect obstructive and restrictive lung diseases in patients, such as emphysema, pulmonary fibrosis, or asthma, based on distinct temporal changes [6].

Furthermore, TLV [7] has been proven to correspond with mortality rate and health status. Currently, the most significant measurement of TLV is the Pulmonary Function Test (PFT). It utilizes non-conventional techniques such as body plethysmography, helium, and nitrogen dilution techniques. In [8], they have demonstrated that TLV obtained from CT scans is highly associated with TLV obtained from PFTs. On the other hand, predictive equations have grown into a prominent pathway to investigate TLV estimation from CT scans. This has been the area of interest in research for over a century, with the first relevant paper using the gas dilution technique to demonstrate the correlation of external measurements to the PFT. Previous papers were based on either the use of planimetric techniques or the estimation of a specific geometry or several manual linear measurements. However, these approaches have two drawbacks which are relying on manual measurements to estimate TLV and small sample

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sizes, resulting in unclear conclusions if the techniques could be generalized for different applications.

Following the above discussions and inspired by the CNN model, we study the role of TLV labels based on thoracic CT imaging in deep learning training. We develop a deep learning-based software system by optimizing various state-of-the-art deep-learning approaches to automatically determine TLV using a large dataset of medical lung CT scans, curated for the Vietnamese market. Until now, there exists various commercial software worldwide [9] with similar working mechanisms to aid medical specialists to calculate lung volume and simulate lung diagrams. However, the cost has proven to be too high, and the language interface makes it difficult for local users who do not speak English. Moreover, such software is constructed to be compatible with only the CT images produced by the company itself, and we could not attain access to the system's actual accuracy and algorithm. To solve this problem, we propose a localized software that applies a machine learning approach for lung partitioning, 3D model reconstruction, and lung volume calculation. The effectiveness of our algorithm is evaluated by comparing calculated results from this research with actual patient data collected from Bach Mai hospital.

The paper is organized as follows: the first part introduces the proposed method including deep learning-based lung segmentation, 3D images reconstruction, and lung volume calculation, the second part shows the interface details, how to display and work of the proposed software, the final part concludes the paper with experimental results, discussion, and evaluation.

2. Proposed Model

The proposed method used in the software of the paper is shown in Fig.1 as below:

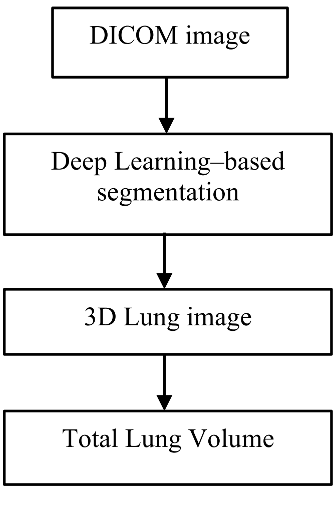


Fig. 1. Proposed method

The proposed method consists of three major steps: (1) Deep learning-based segmentation, (2) 3D Reconstruction process, and (3) TLV. Our proposed deep learning model is based on BCDU-Net, and Convolutional Neural Network (CNN). In the following parts, we will introduce deep learning-based segmentation, followed by the segmentation stage to prepare data for 3D reconstruction and volume calculation. Then, we describe the automated 3D reconstruction process. Finally, we describe step-by-step the deep-learning-based software used to calculate the TLV of these images, with the corresponding masks.

2.1. DICOM Images Dataset

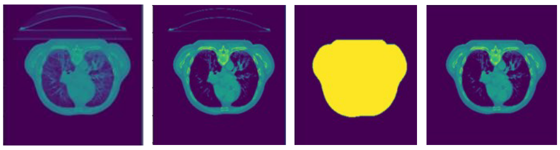
In this research, we use The Cancer Image Archive (TCIA) dataset [10]. The dataset contains 4DCT images of 60 patients, provided by three institutions for the Lung CT Segmentation Challenge in 2017. The participants were selected based on having thoracic diseases and radiation treatment planning. The CT images of those patients were then acquired for the auto-segmentation algorithms grand challenge and made available on TCIA for the public. The images are provided in DICOM format and have resolutions of approximately 512 x 512 pixels. The data consists of 36 training datasets, 12 off-site test datasets, and 12 live test datasets, which sums up to a total of 9,593 images. All ground truth was manually extracted and obtained from the clinic that used them for treatment planning. They were then reviewed (edited if needed) by the RTOG 1106 contouring atlas to ensure consistency among the 60 patients. Our utilized dataset only contains 36 training datasets and 12 live test datasets. Each training dataset is labeled as LCTSC-Train-Sx-yyy, with Sx and yyy representing the institution and the dataset ID in the institution respectively.

Similarly, each live testing dataset is labeled as LCTSC-Test-Sx-20y, with Sx and 20y representing the institution and the dataset ID in the institution respectively.

2.2. Deep Learning Segmentation

Data Pre-processing

The pre-processed CT lung images as shown in Fig.2. In this stage, we prepare the data by pre-processing the raw input images to optimize the training results of the deep learning network. We have also changed the channels of the images to prepare them for training and testing. Since numerous redundant objects are observed in the CT scans such as bones and air, it has a substantially negative impact on the segmentation procedure. Hence, we propose an algorithm that utilizes thresholding and dilation morphological operations to extract only Regions of Interest (ROI). This allows for more efficient training and a significant reduction of false-positive results, which enhances the speed and accuracy of the training process.



Input Optimized ROI Pre-processed

Fig. 2. Pre-processing on Lung dataset

We apply the dilation morphological process, and threshold-based model to the CT scans. To improve the overall segmentation result and forecast, we increase the focus of the network to train only a series of specific image features. The ROI is displayed in black, which can be seen in the "Optimized" image. Then, we apply HU ranges (-512, 512) and morphological operation to extract the ROI of the scans. This is shown in the third image. The final image shows the result of the pre-processing stage where all redundancies are efficiently removed.

Deep Learning Segmentation

Based on the application of BCDU-Net, we would like to present, discuss, and apply the results in this research paper. We developed a deep-learning-based technique mainly inspired by BCDU-Net to automatically segment the medical lung CT scans. We took full advantage of the U-Net architecture, bi-directional ConvLSTM (BConvLSTM), and the working of dense convolutions layers. The Dense Convolutions Layer of the BCDU-Net model is shown in Fig. 3.

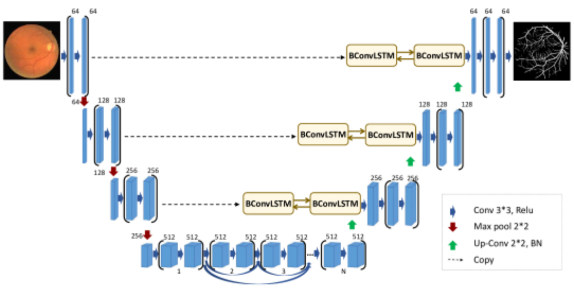


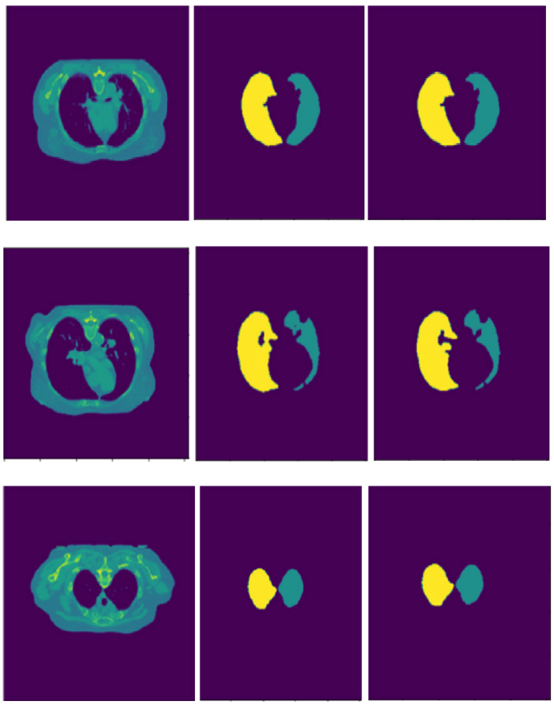
Fig. 3. Bi-directional ConvLSTM BCDU-Net with skip connections

BCDU-NET encompassed four stages of two 3 × 3 convolutional filters each in the encoding path. Each convolution filter is followed by a 2 × 2 max-pooling and a ReLU activator. These three layers together form a down-sampling process, wherein feature channels are doubled. This ensures that the representation of images is gradually extracted along the encoded path and its dimensions are increased layer by layer. This model has two advantages compared to other U-Net-based segmentation approaches: (1) The learning redundant features problem is generally prevented by the application of densely connected convolutions in the last successive convolutions of the U-Net encoded path layer. (2) Each up-sampling stage in the decoding path is followed by Batch Normalization (BN), which has been proven to improve the performance, speed, and stability of neural networks. The outputs from the batch normalization function are combined and fed to a Deeper Bi-directional Convolutional LSTM (BConvLSTM) to collect spatiotemporal information. BConvLSTM applies forward, and backward ConvLSTMs [11] on the input data in two layers, which enhances feature extraction by encouraging information flow along bi-directional streams.

Results

We tested and trained our proposed neural network on CT images of the TCIA dataset of the 2017 Lung Segmentation Challenge with the corresponding given ground truth and annotated lesions as described in the above section. The network was trained from scratch for all datasets. The results show that our proposed method is better than the current alternative models with an overall accuracy of 99.80%.

This dataset contains thoracic CT scans of the Lung in DICOM format with assigned labels for lung segmentation. We use 36 training datasets for training and 12 live test datasets for testing the proposed method, the size of all images needs to resize to 256 x 256 because the input of the model is 256 x 256 pixels. We train the model on these scans with their corresponding masks as well as for the testing phase and estimate the lung region as an ROI inside the estimated surrounding tissues. Fig. 4 shows three segmentation outputs of the proposed network for the TCIA lung dataset that we described above.



Input GT BCDUNet

Fig. 4. Segmentation results of BCDU-Net on TCIA dataset

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2.3. 3D Reconstruction

With the collected images from the segmentation process, we have obtained separated right and left lung masks. From there we propose to apply that mask in building a 3D lung prototype. This process applies the Marching cube algorithm to build the 3D model. This algorithm is often adopted in medical visualizations such as CT and MRI images, for special effects or 3D modelling.

The algorithm [12] proceeds through the scalar field, taking eight neighbouring locations at a time (thus forming an imaginary cube), then determining the polygon(s) needed to represent the part of the surface that passes through this cube. The individual polygons are then fused into the desired surface as shown in Fig. 5.

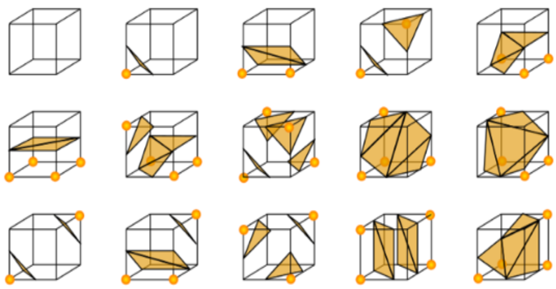
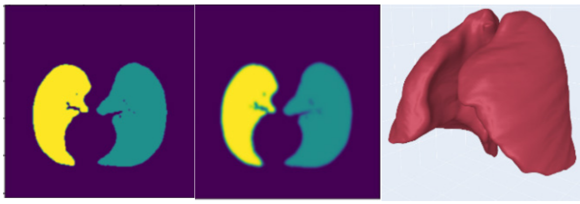


Fig. 5. Look up table of marching cubes: 15 different configurations

This is accomplished by treating each of the 8 scalar values as a bit in an 8-bit integer to create an index to a precalculated array of 256 possible polygon configurations (2^8=256) within the cube. The appropriate bit is set to one if the scalar value is higher than the ISO-value, and to zero if it is lower. The actual index to the polygon indices array is the last value after all eight scalars have been checked.



a) b) c)

Fig. 6. Lung 3D reconstruction process. a) Slice of lung mask; b) After using Gaussian filter; c) 3D Lung image

Based on the above application of the Marching cube algorithm, this algorithm extracts various parts of the cubes from images to build a 3D model. Due to the triangular angle of the proposed algorithm, the 3D model might possess a rough shape. As such, we apply the Gaussian filter to blur out rough edges before feeding the model into the algorithm. After that, all cubes with their remaining triangular shapes are loaded through the entire lung volume to get the 3D model. The whole process is presented in Fig. 6.

From the actual patients' data collected from the hospital, we found that they contain an inconsistent level of thickness. We pick the ones with a thickness of 5 mm since 5 mm allows easier infusion in 3D partitioning and reconstruction. Then we employ the interpolation formula Equation (1) as shown below to create multiple 1mm-thick slices with adjustable thickness.

$$Y = \frac{(Y_2 - Y_1)}{(X_2 - X_1)} * (X - X_1) + Y_1 \qquad (1)$$

Equation (1) is a linear interpolation between two known points. If the two known points are given by (x_0, y_0) and (x_1, y_1), the linear interpolant is the straight line between these points. For a value x in the interval (x_0, x_1), the value y along the straight line is given from the equation (1). This formula goes through each 5mm slice to generate an interpolated linear equation, from which the points of the 1mm slice are inferred.

This allows us to improve the accuracy of 3D model reconstruction. Fig. 7 shows the results of the application of the interpolation formula to obtain slices from 1 mm to 5 mm thickness.

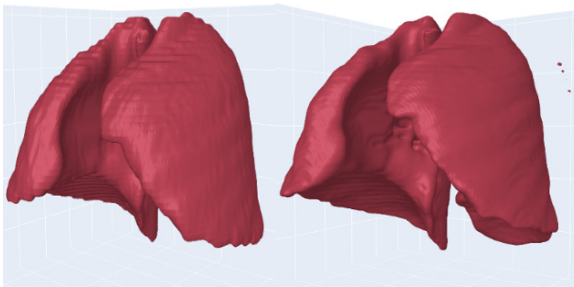


Fig. 7. Interpolation of lung slices (1 mm to 5 mm thickness)

2.4. Measurement of Total Lung Capacity

After segmentation, we successfully collected the total value of the lung mask. Fig. 4 illustrates the visual presentation of an extracted lung mask. Blue and yellow sections are the right and left lungs respectively. Since CT images contain voxel, this means that it attains three-dimensional measurements which are length, width, and height (in mm). Next, we multiply those newly found parameters together to gain the volume of the voxel (in mm^3). To calculate total lung capacity, we loop through the entire CT scans dataset to obtain the total amount of voxels. As the final step, we multiply the mask area by the voxel volume, resulting in the TLV.

3. Proposed Software

Computer-aided diagnosis systems based on artificial intelligence (AI) play a key role in the early identification and diagnosis of suspected and confirmed respiratory diseases. For our software, the default languages are especially set to both Vietnamese and English. The combination of data pre-processing and deep learning - based segmentation creates a novel way to build a multitasking software, capable of automatically partitioning the lungs, reconstructing 3D images, and calculating TVL.

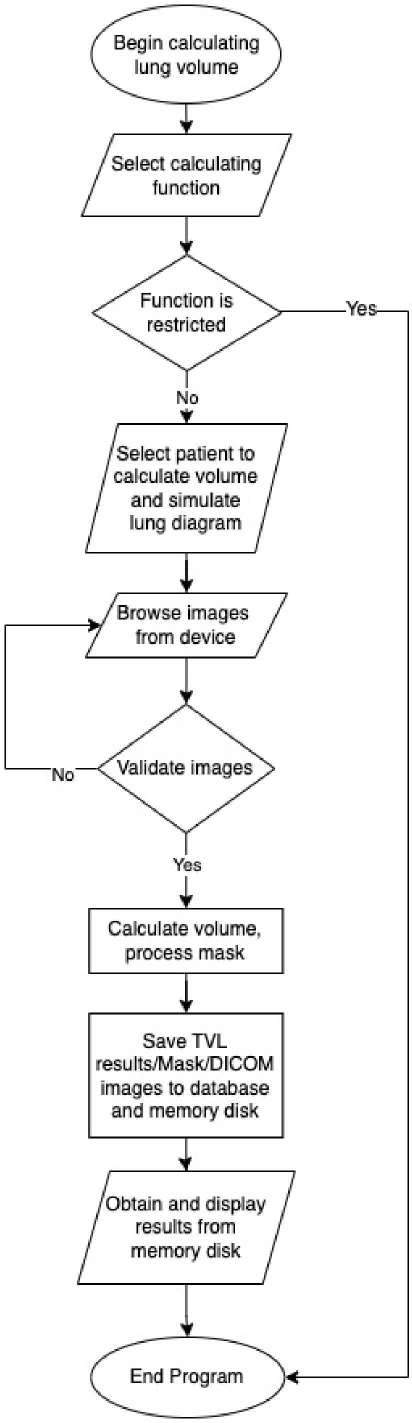


Fig. 8. Algorithm diagram of the software

We design the website with the utmost convenience of our users in mind. The software is built in the form of a web application, using Python as the backend language together with Django framework and Restful API. The front end of the website is written using JavaScript language and VueJs framework providing a friendly graphical user interface for physicians and patients. Thus, our proposed software is characterized by easy navigation, organized sections, and especially the option for Vietnamese language, which most state-of-the-arts medical software lack. For database storing, PostgreSQL is utilized.

Furthermore, we would also set up a step-by-step guidance system as well as a 24/7 support centre. The working mechanism of the software is outlined as presented in Fig. 8.

Firstly, a new patient would be registered to the system with all the essential information. Fig. 9 displays the interface of this function. Then, the program to calculate TLV could begin. User selects the calculating function that is not restricted to access.

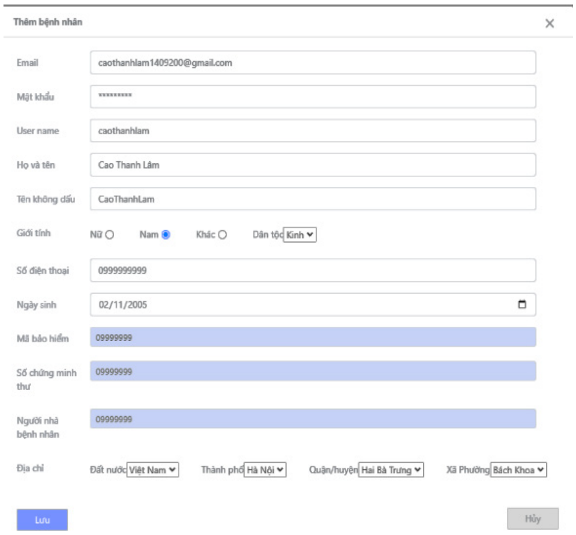


Fig. 9. Patient is added to the electronic medical records

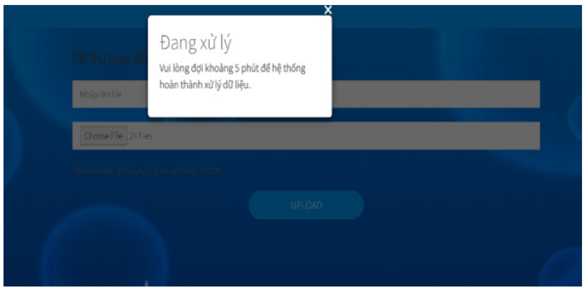


Fig. 10. DICOM Image Uploading Process

Next, DICOM images of the patient are uploaded to the software (Fig. 10). Images can be browsed directly from the device or other forms of digital storage.

Each image will be validated according to format and several parameters of a DICOM scan. Whether the image is compatible and successfully uploaded to the system, a message will be returned to the user's screen.

Once the image is accepted into the software, the image will go through the above-mentioned process to form a lung mask. Time taken to process the image is directly proportional to the quality of the image. The higher the quality, the longer the processing time.

After the image has been completely processed, it will be fed into the previously trained deep learning - model. This purpose of this step is to produce the masks of the lung based on the DICOM CT images. Furthermore, user has the ability to display individual part of the lung (left, right, TLV), aside from displaying 3D lung simulations.

Fig. 11 illustrates our results of automated 3D lung simulation. User can choose the whole lung, the left side, or the right side, thus, allowing users to have the most comprehensive view of the actual shape of the lung.

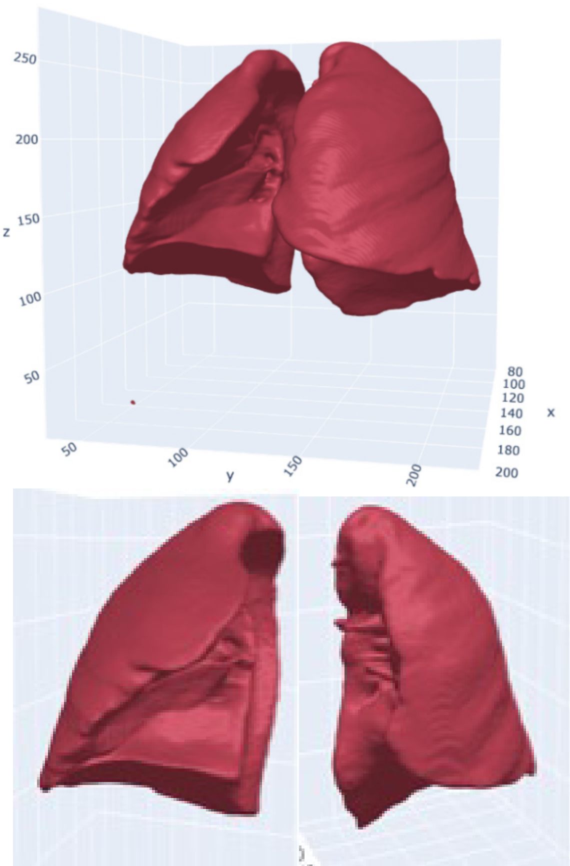


Fig. 11. 3D Lung simulations

Furthermore, our simulation of the lung could attain a better evaluation of the surface lesions, leading to an improved diagnosis and, subsequently, better treatment plan. Previous CT analysis reports can only estimate approximate range of lesions, which cannot be quantitatively concluded. Consequentially, it is arduous to determine the changing course of the lesions and whether the treatment plan is effective. The 3D lung models for TLV calculation proposed by our team can not only be utilized to identify the subtle lesions that are difficult to the human eyes, but also better the accuracy of lung-related diseases screening as well as assist in clinical diagnosis. It can also quantitatively determine the level of involvement of each lung lobe and continuously track the prognosis of the disease course, if there is any.

Based on the lung masks, beside a 3D reconstruction of the lungs could be built and displayed to the users, the software can calculate the left, right and total lung volume as shown in Fig. 12. Those information is very helpful with doctor, that can improve workflow as well as patient care.

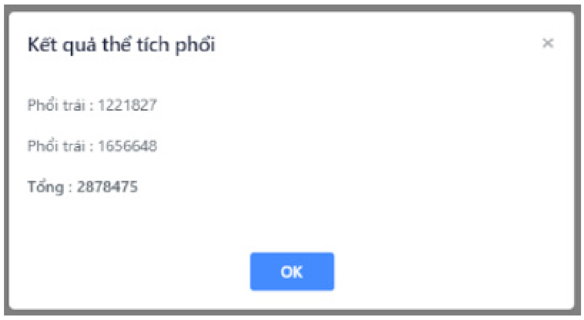


Fig. 12. Automated Lung Volume calculation results

4. Experimental Results

In order to implement this research, we collected the data of 7 patients from the Radiology Centre of Bach Mai Hospital in Hanoi, Vietnam. Information on left, right and total lung volumes was obtained from the software provided by the manufacturer that came with the CT imaging system. This volumetric information provided by the CT imaging device is used by the physician in the diagnostic process, so we use these data as reference data, and are referred to as ground truth (GT) data. Our aim in this test step is to check the accuracy of the proposed algorithm used in the program.

Our work computes the total left lung and right lung from various slice thicknesses. Since the model was trained on 256 x 256 images, individual pixel spacing needs to be doubled in size. Among all the used slice thicknesses, our model produces a superior result with 1mm slices. Table 1 displays the experimental results of our proposed software compared to the ground truth attained from the hospital's software.

We have summarized TLV calculated from our proposed model and from ground-truths of 7 patients as well as the Accuracy in Table 1. Accuracy is the simplest and most used statistical validation metric to evaluate how reliable the results are. It is applied to count the proportion of correct predictions. It could be calculated using the following equation:

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + FP + FN + TN)} \tag{2}$$

Table 1. Lung volume calculation summary

Patient	GT Lung volume (ml)	Lung volume (ml)	GT Right lung volume (ml)	Right lung volume (ml)	GT Left lung volume (ml)	Left lung volume (ml)	Accuracy (%)
1	2784	2912	1601	1685	1183	1227	95.71
2	3886	3918	2041	2039	1845	1879	99.18
3	3363	3334	1668	1649	1695	1685	99.13
4	2946	2962	1511	1528	1434	1443	99.46
5	5222	5229	2800	2774	2421	2455	99.87
6	3136	3118	1737	1736	1399	1382	99.42
7	6457	6473	3600	3615	2857	2858	99.75
Overall Accuracy							98.93

According to Table 1, the results of our software provide nearly identical results with a deviation of only less than 1% in accuracy from the ground truth of 6 patients. We obtained approximately 98.93% accuracy across all patients when compared with results obtained from commercial software. That proves the high efficiency of our proposed software when comparing actual results from Bach Mai hospital.

5. Conclusion

In summary, with the introduction of a modified Bi-directional Convolutional (ConvLSTM) U-Net (BCDU-Net) neural network, we have been able to build an automatic software system to measure TLV with highly accurate results at a low cost. We are able to address the challenge that Vietnamese doctors are having in diagnosing and treating lung-related diseases. In addition, the 3D model reconstruction of the lung has been proven to hold an essential role in aiding medical specialists in early detecting and monitoring lung diseases. Our proposed BCDU-Net-based software for medical image applications has shown exceptional performance in relation to the proposed equivalent state-of-the-art methods. Specifically, our system offers additional features aimed at Vietnamese users, such as allowing Vietnamese as a default language. Furthermore, we addressed the issue of the extremely high cost that most medical instrumentation face. This is critical in achieving our goal of introducing new affordable biomedical software based on AI applications to a broader market in Vietnam.

Acknowledgments

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