

Mathematical morphology based lung segmentation using multiscale dense pyramid network architecture

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Abstract

Chest radiographs (CXR) are widely used technique in healthcare for the diagnosis and treatment of patients. The recognition of visual irregularities from CXR is most difficult task for expert radiologists as the chest area composed of many sensitive anatomical structures. In this paper, a reliable and secure fully automated mathematical morphology-based architecture (M2LS-Net) is designed for extracting lungs region from CXRs. This method uses dense and multiscale features to segment lungs from chest followed by the use of morphological features to eliminate the non-lung regions to enhance the accuracy of the segmentation. The designed method has attained better performance in comparison to established architectures when evaluated against different performance metrics.

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1. Introduction

Pulmonary infections are very usual for the reason that of polluted air and chemicals released by productions units. These are one of the main reasons behind loss of lives throughout across the world. Hence, it become imperative to make a diagnosis of various lung diseases like tuberculosis, lung nodules etc. Lung features can be extracted using various medical imaging tool and techniques like CXR, Commuted Tomography, etc. CXR is a common method used by diagnostic experts for representing the images of affected region such as chest area as it is time and cost efficient and such imaging tools are not affected by external factors while the identification of lung infection in comparison to other tools and techniques [1]. CXR helps in locating the position and severity of any abnormality connect to recurring situation of lungs. CXRs are highly recommended for initial and follow-up examinations in diagnosing various chest diseases due to its effectiveness as an initial diagnostic tool [2]. However, the use of CXRs for diagnostic purposes requires exceptional skill of radiologists as they process huge amounts of CXRs.

The quick and accurate diagnosis of different lung diseases has resulted in a significant decline in the death rate. For this reason, researchers have put in a lot of efforts in designing automated /semi-automated methods to segment lung regions from different types of medical images. The preliminary efforts to assist radiologists in assessing CXRs include the design of a computer-aided diagnosis (CAD) system [3] and efforts have been made to enhance the accuracy of CAD. However, their commercial viability is limited by human intervention and less accuracy. The performance of traditional CAD systems deteriorates due to mannual feature extraction mechanism which results in an error in subsequent processing tasks . Enhancement of computational techniques has enabled the development of modern CAD systems that can handle voluminous CXRs with precision. These systems can automatically segment the lung region Furthermore, various diseases often alter the texture of lung regions which results in poor contrast between the lung area and the rest of the region.

Therefore, to address the above-mentioned challenges in lung segmentation, an automatic M2LS-Net is proposed. The proposed method uses morphological [4] and dense multiscale features to segment lung regions. The key contributions of this paper includes (i) a novel M2LS-Net, an encoder-decoder architecture, (ii) The introduction of two ASP (Atrous spatial pooling) to capture multiscale conceptual features to enhance the

accuracy. In addition to this, the use of an attention mechanism in the skip connection of decoder blocks (iii) The use of morphological features to segment non-lung regions further enhances the accuracy of the M2LS net. (iv) The M2LS-Net is examined and validated on two publicly available datasets of CXRs namely JSRT and Indiana. Rest of this article is structured as follows: The dataset and the presented methodology are illustrated in Section 2. The proposed architecture is depicted in Section 3. Experimental results are presented in Section 4. Finally, Section 5 discusses the future scope and conclusion. Most of the lung segmentation models are designed to extract lung features from concerned medical images with the aim of obtaining accurate lung region but with low weightage on expensiveness of computation. To overcome all discussed challenges and to increase accuracy, in this paper, a novel M2LS net based on mathematical morphology and dense multiscale features is proposed.

2. Proposed methodology

The proposed methodology used for the lung segmentation from CXRs consist of three steps: pre-processing, segmentation of lungs using M2LS, and evaluation of performance on different quantitative parameters. The CXR images are obtained from the publicly available dataset of JSRT [5] and Indiana [6]. The JSRT dataset contains 50 CXR of size 256×256 in RGB color space along with reference images. The Indiana dataset contains more complex 56 CXRs of size 2838×2320 along with reference data. To reduce the computational complexity, the CXRs of the Indiana dataset are resized to 256×256 and placed together with JSRT data. To eliminate the issue of overfitting and to enhance the generalizing ability of the model, the data is augmented via some operations such as `shiftscaleRotate`, `HueSaturationValue`, random brightness and contrast etc. Finally, the dataset is splitted into training and validation samples.

2.1 Preprocessing

The CXRs are obtained from different types of sensors and suffer from the noise engendered by various types of noises which alters contrast and texture of the images. In this work, these issues are handled by median filtering and Texture contrast enhancement. These steps are discussed below.

2.1.2 Median filtering

In the work presented here, the noise present in CXRs is removed by the non-linear filter median filter which overcomes the issues of linear filters. The median filter is a widely used nonlinear filter that eliminates the outliers without losing the sharpness of the objects at the edges. The median filtering operation is explained as,

$$\text{Im}(x, y) = \text{med}\{I(i, j) | (i, j) \in W\} \quad (1)$$

2.1.3 Texture transformation via Adaptive Contrast enhancement

The thoracic cavity contains various organs that alter the lung region texture which reduces the contrast of the images. The low-contrast images are not suitable for precise lung segmentation. To address the issues related to texture and contrast the adaptive contrast enhancement is used. The median filtered color CXR image is first converted into $L^*a^*b^*$ color space as per Eq. (2)

$$\begin{aligned} L &= 0.2126 * R + 0.7152 * G + 0.0722 * B \\ a &= 1.4749 * [0.2213 * R - 0.3390 * G + 0.1177 * B] + 128 \\ b &= B = 0.6245 * [0.1949 * R + 0.6057 * G - 0.8006 * B] + 128 \end{aligned} \quad (2)$$

After performing an adaptive transformation on the CXR image of the L^* layer, the image is transformed back into XYZ colour space followed by transformation into RGB color space, this transformation is represented as,

$$\begin{aligned} X &= 96.42 f^{-1} \left(\frac{L^*+16}{116} + \frac{a^*}{500} \right), Y = 100 f^{-1} \left(\frac{L^*+16}{116} \right), \\ Z &= 82.5188 f^{-1} \left(\frac{L^*+16}{116} - \frac{b^*}{200} \right) \end{aligned} \quad (3)$$

$$\text{Where } f^{-1}(t) = \begin{cases} t^3 & \text{if } t > \frac{6}{29} \\ \frac{108}{29} \left(t - \frac{4}{29} \right) & \text{else} \end{cases}$$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 2.3706743 & -0.9000405 & -0.4706338 \\ -0.5138850 & 1.4253036 & 0.0885814 \\ 0.0052982 & -0.0146949 & 1.0093968 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \quad (4)$$

3. M2LS-Net Architecture

The proposed M2LS-Net architecture is designed on the strengths of residual mechanism, multiscale features through ASP and attention mechanism. The block diagram of the proposed M2LS-Net is shown in Figure 1, The encoder of M2LS-Net contains one stem block followed by four residual blocks, each block has a two consecutive (3 × 3) convolutional block and mapping function. In between the encoder and decoder paths two Atrous Spatial Pooling (ASP) blocks are placed which act as a bridge and collect multi-scale features. The decoder path consists of three residual blocks, having an attention mechanism at skip connections to enhance the effectiveness of feature maps.

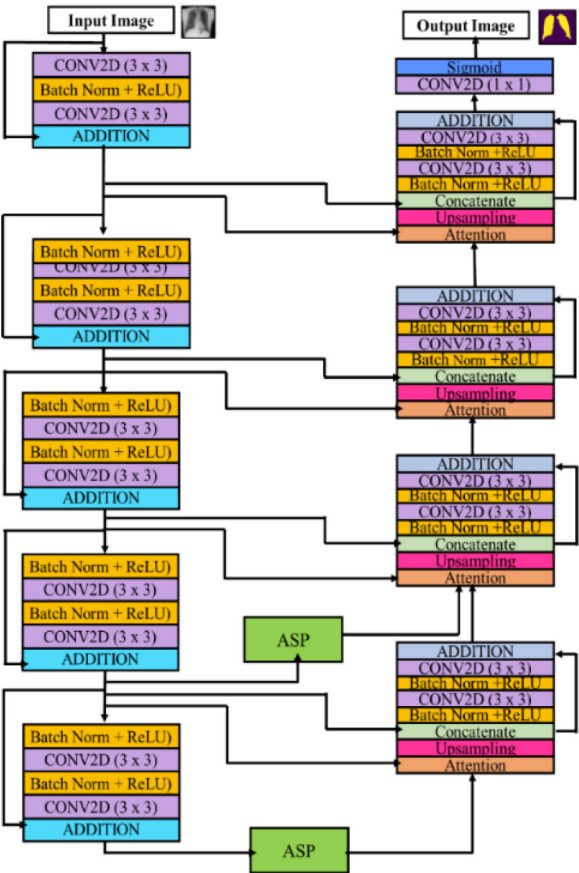


Figure 1

Architecture of Proposed M2LS-Net

3.1 Residual Block

To overcome the exploding gradient problem, a residual network was introduced [7]. This block incorporates the residual connections where the output of the preceding layer is added with the output of the immediate next layer to propagate more discriminated features without further degradation. The residual block is defined as below:

$$r = f(x.W_i) + x \quad (5)$$

Here x , r represent input and output vectors respectively and $f(x.W_i)$ denotes the residual learning reformulation in the network.

3.2 Atrous Spatial Pooling(ASP)

The ASP [8] block is used to extract multiscale contextual feature maps from the input feature map $f_{in} \in \mathbb{R}^{H \times W \times C}$ through three dilated convolutional operations. The output of dilated convolutional operations is concatenated to fuse the feature maps and generate the output $f_{out} \in \mathbb{R}^{H \times W \times C}$. In this model ASP is used as a bridge between the last two blocks of the encoder and decoder part respectively as shown in Fig. 2. The operation of the ASP block is represented as,

$$f_{out} = f_1[f_{r_1}^k(f_{in}); f_{r_2}^k(f_{in}); f_{r_3}^k(f_{in})] \quad (6)$$

Where f_r^k represents a dilated convolutional operation with r dilation factor and kernel of size $k \times k$.

3.3 Attention Block

In this research work, we have proposed a model integrated with ASP module for extracting features [9] with multi-receptive fields [10]. It takes 2 inputs, one is a activation map from the dense layer (x) and other one is the attention signal (g). Attention factor (α) $\in \{0, 1\}$ for extracting the target object of interest. The result of the attention factor is a convolution of given activation map ($x_{i,c}^L$) and α and can be represented as,

$$\hat{x}_i^L = x_{i,c}^L \cdot \alpha_i^L \quad (7)$$

The incorporation of the attention mechanism removes the unenviable info and increase the confined details.

3.4 Loss function

Binary cross entropy loss function (BCE) is utilised to assess the effectiveness of semantic segmentation. In this work, binary cross entropy loss (BCELOSS) is used as the objective function. Let $Predimg_i$ is the segmented lung region from Org_i image and GT_{img} represent the reference lung region. then the BCE can be computed mentioned below,

$$BCELOSS(Predimg_i, GTimg_i) = -\sum_{(i=1)^r} \sum_{(j=1)^c} [(GTimg_i(i, j) \times \log Pred_i(i, j)) + (1 - GTimg_i(i, j)) \times \log(1 - Predimg_i(i, j))] \quad (8)$$

Where $Predimg_i(i, j)$ and $GTimg_i(i, j)$ represent the pixel value at i^{th} row and j^{th} column.

3.5 Post Processing using mathematical morphology

The lung region extracted by the proposed M2LS-Net suffers from issues such as some non-lung regions are also segmented as lung region and some holes. These issues are efficiently handled by morphological operation such as opening and closing defined as;

$$X \circ Y = (X \ominus Y) \oplus Y \quad (8)$$

$$X \circ Y = (X \oplus Y) \ominus Y \quad (9)$$

Here X is the binary image and Y is structuring element. These operations are combination of $\ominus$ (erosion) and $\oplus$ (dilation) operations respectively.

4. Experimental results

In this section, the experimental results of M2LS-Net are discussed. For measuring the performance of segmenting lungs from CXRs, evaluation matrices. These evaluation metrics includes precision (L_{prec}), recall (L_{recall}), $F1$ -score, Accuracy (L_{acc}) and Jaccard Similarity coefficient (JSC). The resized CXRs was provided as an input to the M2LS-Net. The dataset was split into training and testing in 90:10 ratio with respective masks and M2LS-Net is compiled with Adam optimizer with the learning rate of 0.001. The M2LS-Net is trained for 50 epochs having batchsize of 4. Experimental results are on JSRT and Indiana Dataset depicted in Figure 2 and Figure 3 respectively. The CXR images are exhibited in Figure 2 (a1) - (a4) and Figure 3 (a1) - (a4), and the resultant ground truth are represented

in Figure 2 (b1) - (b4) and Figure 3 (b1) - (b4). The lung area obtained by M2LS-Net is shown in Figure 2 (c1) - (c4) and Figure 3 (c1) - (c4). The performance of the M2LS- are presented in Table 1 and Table 2.

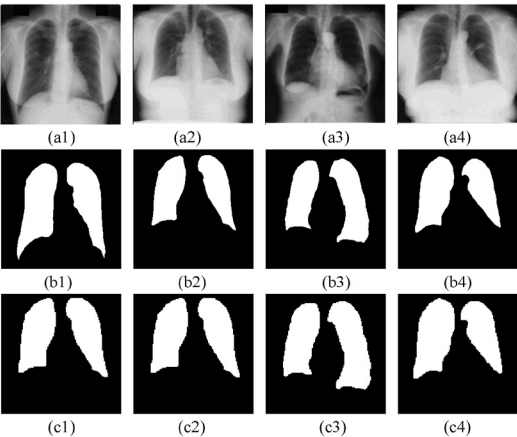


Figure 2

Experimental results of the proposed M2LS-Net on JSRT Dataset.CXRs (a1)-(a4), corresponding ground truth (b1)-(b4),segmentation result after postprocessing (c1) -(c4)

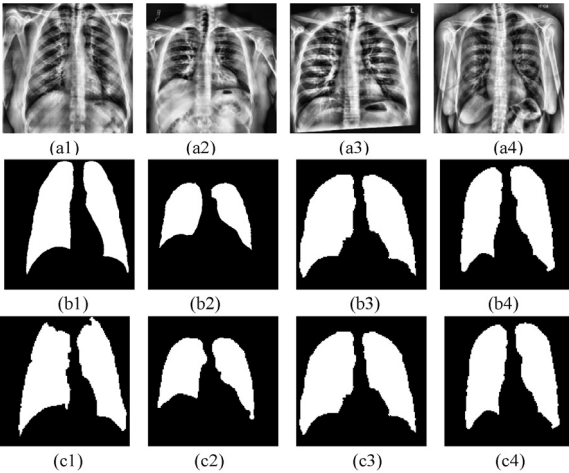


Figure 3

Experimental results of the proposed M2LS-Net on Indiana Dataset. CXR (a1)-(a4), corresponding ground truth (b1)-(b4),segmentation result after post processing (c1)-(c4)

Table 1
Performance of M2LS-Net on JSRT Dataset

	<i>Lprec</i>	<i>Lrecall</i>	<i>F1-score</i>	<i>Lacc</i>	<i>JSC</i>
Figure 2 (a1)	0.99	0.97	0.97	0.9834	0.98
Figure 2 (a2)	0.97	0.96	0.98	0.9884	0.99
Figure 2 (a3)	0.98	0.97	0.98	0.9851	0.98
Figure 2 (a4)	0.99	0.96	0.94	0.9761	0.99

Table 2
Performance of M2LS-Net on Indiana Dataset

	<i>Lprec</i>	<i>Lrecall</i>	<i>F1-score</i>	<i>Lacc</i>	<i>JSC</i>
Figure 3 (a1)	0.95	0.95	0.95	0.9461	0.86
Figure 3 (a2)	0.98	0.97	0.97	0.9747	0.89
Figure 3 (a3)	0.96	0.95	0.95	0.9523	0.87
Figure 3 (a4)	0.97	0.97	0.97	0.9714	0.92

The accuracy of the M2LS-Net model on training and validation data during 50 epochs is visualized in Figure 4 (a) and validation and training loss using *BCELOSS* function is shown in Figure 4(b).

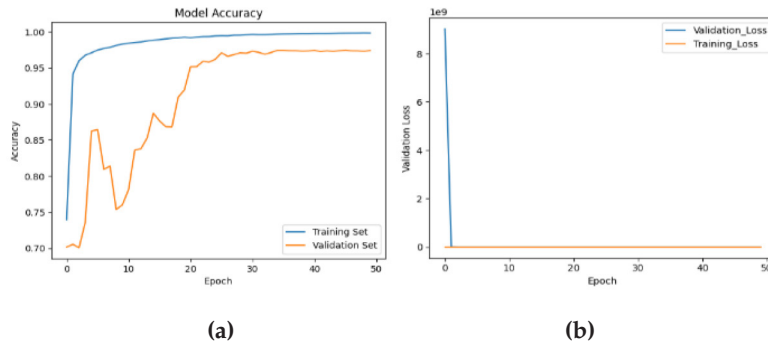


Figure 4

**Performance of M2LS-Net (a) Model's accuracy during training and validation
(b) training and validation loss**

5. Discussion and Conclusion

In this paper, a fully automated mathematical morphology-based architecture (M2LS-Net) is proposed to segment lungs from chest

radiographs. In the first step, CXRs obtained from JSRT and Indiana dataset are preprocessed to eliminate the noise and to enhance the texture contrast to highlight the lung region. The proposed M2LS-Net uses residual learning to delineate features and APS block is used as a bridge in between the encoder and the decoder to capture contextual multiscale features. Furthermore, the computational complexity is reduced by the attention gate mechanism. The performance of M2LS-NeT is further increased by morphological operations which eliminates the misclassified lung regions. The experimental results are presented visually and evaluated on different evaluation metrics such as L_{prec} , L_{recall} , $F1$ -score, L_{acc} and JSC . The proposed method has achieved outstanding results in both dataset (JSRT and Indiana).

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