Segmentation of lung fields from chest radiographs-a radiomic feature-based approach

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Abstract

Precisely segmented lung fields restrict the region-of-interest from which radiological patterns are searched, and is thus an indispensable prerequisite step in any chest radiographic CADx system. Recently, a number of deep learning-based approaches have been proposed to implement this step. However, deep learning has its own limitations and cannot be used in resource-constrained settings. Medical systems generally have limited RAM, computational power, storage, and no GPUs. They are thus not always suited for running deep learning-based models. Shallow learning-based models with appropriately selected features give comparable performance but with modest resources. The present paper thus proposes a shallow learning-based method that makes use of 40 radiomic features to segment lung fields from chest radiographs. A distance regularized level set evolution (DRLSE) method along with other post-processing steps are used to refine its output. The proposed method is trained and tested using publicly available JSRT dataset. The testing results indicate that the performance of the proposed method is comparable to the state-of-the-art deep learning-based lung field segmentation (LFS) methods and better than other LFS methods.

Keywords Radiomic features · Lung field segmentation · Chest radiographs

1 Introduction

Medical images acquired using different imaging modalities are used in diagnosis, staging, and restaging of various diseases. While advancements in technology have improved the quality and speed of acquiring medical images a lot, the detection of diseases at an early stage has not comparably improved. This is due to multiple factors such as tendency to impulsively treat more common diseases, inaccessibility to diagnostic facilities, lack of domain expertise in primary healthcare centres (PHCs) and secondary healthcare centres (SHCs), heavy rush of patients in tertiary healthcare centres (THCs) and super-speciality hospitals. To overcome these limitations, computer-aided diagnosis (CADx) systems for different diseases such as tuberculosis (TB) [13], lung cancer [3], breast

cancer [1], prostate cancer [9] have been proposed that can assist clinicians in screening, diagnosis, staging, and therapeutic decisions.

In a chest radiographic computer-aided diagnosis (CADx) system used for detection of various chest pathologies such as TB, pneumothorax, pleural effusion, segmentation is the initial step performed to extract the lung region or the *lung fields*. The precise segmentation of lung fields is extremely important because it defines the region-of-interest (RoI) in which specific radiologic signs such as lung nodules, pulmonary opacities, cavities, and consolidations are searched. However, lung field segmentation (LFS) is extremely challenging due to various reasons such as (i) overlapped anatomical structures like the heart, rib-cage, and clavicles, which results in ambiguous lung boundary, (ii) variation in shape and size of lungs due to gender, age, and physical structure of the patient, (iii) presence of foreign objects such as brassier clips, buttons, pacemakers, and catheters, and (iv) various radiographic artifacts.

To solve this challenging task, a number of LFS methods, classified as rule-based methods, pixel classification-

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based methods and deformable model-based methods, have been presented. Pixel classification-based methods are further classified as shallow learning-based methods and deep learning-based methods. Deep learning-based methods have the advantage that the feature extraction process in these methods is hierarchical and automatic, but have the limitation that they require a large training dataset and higher computational power. Since annotated medical image data is scarce and medical systems generally do not have the desired computational power, deep-learning based methods are not always preferred. On the other hand, shallow learning-based methods extract user-specified radiomic features from chest radiographs, colloquially known as chest X-rays (CXRs), to classify each pixel as either belonging to the lung or non-lung region. They use *radiomics* to extract high dimensional feature data from medical images that describe texture, shape, and intensity of the complete or a part of the image. These features help in creating a predictive model that can be used to detect the abnormalities in the medical images. In this paper, a shallow learning-based method is presented that uses around 40 radiomic features to perform lung field segmentation. The segmented output is refined using DRLSE and other post-processing methods.

The rest of the paper is organized as follows. Section 2 presents a detailed description of lung field segmentation methods presented till date. The proposed shallow learning-based LFS method and the dataset used to train and test it are presented in Sect. 3. The metrics used to evaluate the performance of the proposed method and the experimental results are presented in Sect. 4. Finally, the conclusion is drawn in Sect. 5.

2 Related work

The existing LFS methods can be broadly classified into three main categories, namely rule-based LFS methods, pixel classification-based LFS methods, and deformable model-based LFS methods. The following subsections describe the general working principle of each category, their merits and demerits, and the representative works belonging to each of them.

2.1 Rule-based LFS methods

The methods in this category employ heuristic rules based on lungs' position, intensity, texture, and structural relationship with other anatomical structures to segment the lung field. The rules are formulated from the prior knowledge of lung anatomy and its imaging characteristics. These rules are implemented using low-level image processing operations such as intensity-based thresholding,

edge detection and linking, region growing, and morphological operations. As shown in Fig. 1, a number of rules are generally applied in sequence to obtain the desired result. These methods provide a notable freedom as the underlying rules can be combined in different permutations and combinations to obtain the desired results.

Cheng and Goldberg [7] proposed one of the earliest rule-based LFS method, in which horizontal and vertical profiles (HVP) of the CXR image are analyzed to determine a rectangular box enclosing the lung region. Gray-level histogram thresholding and smoothing operations are then performed to obtain the lung boundary. HVP analysis is also used by several other rule-based LFS methods [8, 11, 15] to initially approximate the lung region. Li et al. [11] used first derivatives of HVP for initial boundary detection, iterative boundary point adjustment algorithm for their refinement, and edge-tracing to eliminate faulty boundary fragments. The method, however, finds difficulty in detecting mediastinal and hemidiaphragm edges due to their complex structure. Duryea and Boone [8] presented a similar approach to segment lung fields in images at a reduced scale. The limitation of the method is that the segmentation uncertainties increase when the segmented regions are expanded to full resolution. Pietka [15] performed histogram analysis, to eliminate the bright mediastinum, sub-diaphragm, and thorax region, before applying HVP analysis and gradient analysis to segment the lung boundary. Instead of using an edge-tracing procedure, Ahmad et al. [21] proposed a rule-based LFS method that uses Fuzzy C-Means (FCM) clustering algorithm to refine lung boundary. The algorithm gives the best performance amongst all rule-based LFS methods.

The rule-based methods are unsupervised and thus do not require scarcely available annotated medical datasets for training. However, these methods provide poor performance when the lung fields are missing, or highly deformed. Moreover, these methods imbibe the knowledge about a particular anatomic structure and its imaging characteristics in form of heuristic rules and thus have a little scope of customization for segmenting other anatomic structures using same rules.

2.2 Pixel classification-based LFS methods

As shown in Fig. 2, pixel classification-based methods use a binary classifier, trained over a large annotated dataset, to classify each pixel of the CXR image as either belonging to lung or non-lung region. On the basis of how features are extracted, these methods are further categorized as (i) shallow learning-based methods, and (ii) deep learning-based methods. The feature extraction process used by shallow learning-based methods is intuitive and hand-crafted. Since, this paper presents a shallow learning-based

Fig. 1 Workflow pipeline of rule-based LFS methods

Fig. 2 Workflow pipeline of pixel classification-based LFS methods

method, only the work related to these methods is presented in this section. For an additional description on deep learning-based LFS methods, readers are advised to refer [14].

The main challenge with shallow learning-based methods is in determining the appropriate class of features to be extracted and extracting them in a robust way. McNitt-Gray et al. [12] were the first to propose a shallow learning-based LFS method and studied the effect of number and quality of features on the classification performance. The proposed method uses three types of features, namely gray-level based features, local difference measures, and local texture measures to characterize the lung field. The method compared the performance of three different classifiers using a complete feature set of 59 features, 8 best features, and 8 random features. It has been deduced that the neural network provides the best performance, and the performance of 8-best features is comparable to the full feature set with significantly less processing time. Ginneken et al. [19] presented a multi-resolution pixel classification method that works at two different image resolutions and has better performance than single-level pixel classification method. Shi et al. [17] presented an unsupervised LFS method in which the objective function of the FCM algorithm is modified by using Gaussian kernel-induced distance metric.

2.3 Deformable model-based LFS methods

These methods represent the shape of the lung field by using a model that can evolve under the influence of internal forces, external forces, and user constraints. The forces are computed from image data; and the constraints about the position, shape, and the appearance are either manually specified or learned from training data. The general workflow pipeline for deformable-model based LFS methods is shown in Fig. 3.

Ginneken et al. [20] proposed an LFS method in which modified active shape model (ASM) approach, based on optimal feature set, is used to find the best displacement for landmarks. In this method, instead of Mahalanobis distance that is used in standard ASM, kNN-classifier is used as the cost function to find the optimal displacement. Shi et al. [16] presented an LFS method in which scale-invariant feature transform (SIFT) technique is used for describing local features and a deformable model based on population as well as patient-specific shape statistics is used. In the initial stages, the output is more dependent on population-based statistics but as more segmentation results are obtained, patient-specific statistics start playing the defining role in constraining the deformable contour.

Level sets method is another deformable framework to represent curves and surfaces using a level set of higher

Fig. 3 Workflow pipeline of deformable model-based LFS methods

dimension scalar function. Annangi et al. [2] presented active contour method (ACM) based on level set with shape priors to perform lung segmentation. Similar to level sets, graph cuts optimization approach is another method in which objective function is minimized. The objective function is defined in terms of boundary, region and object model properties. Candemir et al. [5] presented an LFS method in which content-based image retrieval approach is used to obtain similar training images and then SIFT-flow non-rigid registration is used to create an initial lung model. Graph cuts approach is then used to obtain the final segmented output.

Deformable model-based methods give the best performance out of three classes discussed, however, these methods also have some limitations. Firstly, these methods require boundary initialization. If the initialized boundary is not close to the actual boundary, these methods can get trapped at local minima due to other anatomical regions such as heart, stomach gases (since they have similar intensity characteristics as lung). Secondly, these methods are complex procedures and require setting values of multiple parameters manually for optimal performance.

3 Materials and methodology

3.1 Dataset used

In this study, a publicly available dataset has been used for the training and testing of the proposed method. This dataset is collected by the Japanese Society of Radiological Technology (JSRT) in collaboration with Japanese Radiological Society [18]. It contains 247 CXRs, of which 154 have lung nodules while 93 have none. All the radiographs have a size of 2048×2048 pixels with a grayscale depth of 12 bits and pixel size as 0.175 mm. The manually annotated masks of CXR images are available in the Segmented Chest Radiograph (SCR) dataset created by Image Sciences Institute, Netherlands. In our experiments, half of the dataset, i.e. 144 CXRs, are used for training while the remaining half, i.e. 143 CXRs, are used for the testing purpose.

3.2 Proposed methodology

The proposed method uses the following steps, i.e. pre-processing, pixel classification, and post-processing, sequentially to segment lung field from a CXR.

1. *Pre-processing* To perform training, the lung masks are obtained from the SCR dataset which consists of 1024×1024 images. All the training images and masks are resized to a working resolution of 128×128 pixels. Histogram equalization is then applied for contrast enhancement since the images in the JSRT dataset have poor contrast. The histogram equalization helps in visualizing the lung portion distinctively, thus allowing to obtain accurate lung boundary.
2. *Pixel Classification*: In this step, a specific number of pixels are selected in a symmetric way from each image and then handcrafted features are computed for each of these pixels to form the feature vector. Since the input image is of 128×128 resolution, there are 16384 pixels in each image. Out of these, 4096 pixel samples are obtained from each image (selecting top-left pixel out of every 2×2 pixel block). Different features for these samples are extracted to form a feature set. The following spatial and textural features are used in this study.
 - (a) *Pixel intensity* Intensity of a pixel is one of the basic features characterizing its appearance. For an 8-bit grayscale image, the pixel intensity ranges from 0 (black) to 255 (black).
 - (b) *Pixel coordinates* The spatial coordinates of a pixel, x and y , are significant features in the segmentation of an anatomical structure from a medical image since the location of the anatomical structure within the medical image is generally fixed. They are also used to establish inter-pixel correlation in a localized region within the image.
 - (c) *Gaussian outputs* The Gaussian filter outputs weighted average of pixel's neighbourhood, with the average weight more towards the central pixel. For a pixel $I(x, y)$, the Gaussian output can be computed as $G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$,

where σ is the standard deviation of the distribution. We have applied Gaussian filter with $\sigma = 1, 2, 4, 8, 16$ and neighbourhood size as 3×3 .

- (d) *Gaussian derivatives* The first order and second order derivatives of Gaussian filter are used as features for edge direction and texture directionality. Given a Gaussian function $G(x, y)$, its first derivatives in x and y directions are given as $D_x(x, y) = -\frac{x}{\sigma^2} G(x, y)$ and $D_y(x, y) = -\frac{y}{\sigma^2} G(x, y)$. The second derivatives are obtained by differentiating D_x and D_y with respect to x and y to get D_{xx} , D_{xy} , D_{yx} , D_{yy} .
- (e) *Laws' textural features* Laws used the following vectors to detect various types of textural features. The outer product of these vectors is taken to create 16 2D masks, of which 9 masks are selected after removing the symmetric pairs. The so obtained 9 masks are convolved with the pixel and its neighbours to obtain nine textural features.
- $$L5 = [+1 \quad +4 \quad 6 \quad +4 \quad +1](Level) \quad (1)$$
- $$E5 = [+1 \quad -2 \quad 0 \quad +2 \quad +1](Edge) \quad (2)$$
- $$S5 = [-1 \quad 0 \quad 2 \quad 0 \quad -1](Spot) \quad (3)$$
- $$R5 = [+1 \quad -4 \quad 6 \quad -4 \quad +1](Ripple) \quad (4)$$
- (f) *Sobel gradient* Sobel operator is used to detect vertical and horizontal edges in an image. Sobel gradient is obtained by taking gradient of the output of Sobel operator. The gradient of Sobel operator over 3×3 neighbourhood is taken as features corresponding to horizontal and vertical edge information.
- (g) *Entropy* Entropy is a textural feature which statistically measures the randomness in the image. This operator computes the local entropy of each pixel in a specified neighbourhood.
- (h) *Laplacian of Gaussian (LoG)* LoG over 5×5 neighbourhood is used as a feature to find the areas of rapid change in an image.
- (i) *Local binary pattern (LBP)* The intensity value of a pixel is compared with the intensity value of its 8-neighbours in 3×3 neighbourhood in clockwise or counter-clockwise order. If the center pixel's value is greater than neighbour's value, bit '0' is obtained and otherwise '1' is outputted. This process will give an 8-digit binary number which is then converted to a decimal number, which is the new intensity value of the center pixel and is used as a feature.

- (j) *Gabor filters* Gabor filter is a linear filter used for edge detection at a specified orientation and frequency. It is applied on each pixel using the Eqs. 5–7.

$$F(x, y) = \exp\left(\left(-\frac{u^2 + v^2}{2\sigma^2}\right) * \cos\frac{2\pi u}{\lambda}\right) \quad (5)$$

$$u = x \cos \theta + y \sin \theta \quad (6)$$

$$v = -x \sin \theta + y \cos \theta \quad (7)$$

where (x, y) is the pixel location, θ is the specified rotation, σ is the standard deviation and λ represents the wavelength of the sinusoidal factor.

In addition to the above-mentioned features, many other features such as histogram of oriented gradients, autocorrelation and central moments have also been extracted. However, they are not included in the feature set as they are either redundant or not having any positive impact on the performance of the model. Features are selected cautiously and judiciously so as to avoid the curse of dimensionality.

Feature maps corresponding to a few selected features for a sample image are shown in Fig. 4.

Feature vector is created by appending the extracted feature values column-wise. Features in the vector are then normalized to have zero mean and unit standard deviation. Different classifiers like quadratic discriminant analysis (QDA), support vector machine (SVM) and k-nearest neighbors (kNN) are then trained and their performances are compared. It has been found that the performance of kNN classifier is better than other classifiers and thus it is used to classify the test images in this study. For every test image, all the features are first extracted to form the feature vector and thereafter trained classifier is used to classify each sample pixel of the test image. The output obtained is used as an initial model in the next stage of the technique where a deformable model-based method is applied to improve the performance. The output provided by this stage is important as the performance of the deformable method greatly depends on how accurate the initialization is performed.

3. *Post-Processing* The accuracy of segmented output obtained by applying pixel classification method is sometimes low due to radiographic artifacts and overlapping neighboring anatomical structures such

Fig. 4 Feature maps corresponding to few selected features for a sample image

as clavicles, heart, and diaphragm. To improve the segmentation accuracy, the output is post-processed using a deformable model-based method known as DRLSE. In addition to DRLSE, some other post-processing steps are also applied to remove noise and refine the output. The following is a brief description of the post-processing steps.

- (a) *Distance Regularized Level Set Evolution (DRLSE)* Level sets method [6] provides a deformable framework and is used to represent curves and surfaces by applying the level set of higher dimension scalar function. This approach requires initialization and transforms the original curve into a surface using energy functions. The method has been widely used in the fields of image processing and computer vision. However, the disadvantage of the method is that it typically develops irregularities during the evolution of the level set function which destroys the stability of the evolution.

DRLSE method is proposed by Li et al. [10], in which gradient flow is used to derive the level set evolution. The optimal solution is obtained by minimizing the energy function, which includes a distance regularization term and an external energy, and drives the level set towards the desired positions. The energy function to be optimized is mentioned in 8.

$$E(\Phi) = \mu R_p(\Phi) + E_{ext}(\Phi) \quad (8)$$

where $\mu > 0$ is a constant and $R_p(\Phi)$ is distance regularization term. $E_{ext}(\Phi)$ is the external energy that depends on the selected data. Distance regularization term is defined in Eq. 9.

$$R_p(\Phi) = \int p(|\nabla \Phi|) dx \quad (9)$$

where p is the energy density or potential function and the integration is calculated over the domain D . For image segmentation, edge based image information can be used to define the external energy, as in Eq. 10.

$$E_{ext}(\Phi) = \lambda L_g(\Phi) + \alpha A_g(\Phi) \quad (10)$$

where λ and α are constants. $L_g(\Phi)$ and $A_g(\Phi)$ are edge term and area term, respectively, as determined in Eqs. 11 and 12.

$$L_g(\Phi) = \int g\delta(\Phi)|\nabla \Phi| dx \quad (11)$$

$$A_g(\Phi) = \int gH(-\Phi) dx \quad (12)$$

where δ and H are Dirac delta function and Heavyside function respectively and g is the edge indicator function which is computed in Eq. 13.

$$g = \frac{1}{1 + |\nabla G_\sigma * I|^2} \quad (13)$$

where G_σ is the Gaussian kernel with a standard deviation of σ .

This method is used to provide small improvements over the result of the pixel classification method. In this step, testing is performed with different values of parameters μ , λ , α , σ and hence optimal values are obtained for all these parameters at which the method is giving the best performance. The number of iterations, for which the energy optimization

will be performed, is also set to a particular value after testing.

- (b) *Other post-processing steps* Although the pixel classification and DRLSE methods give proper output, some post-processing is needed to remove noise. Firstly, the image is smoothened by applying the Gaussian filter. After executing the previous step, there may remain small regions or individual pixels in the segmented image which are not part of lung region. These regions or pixels are removed by applying morphological operations in such a way that only two connected regions denoting the left lung and the right lung remain.

4 Experiments and results

4.1 Evaluation metrics

For a two-class segmentation problem, the order of confusion matrix is 2×2 and it consists of four areas namely true positive (TP) area, false positive (FP) area, false negative (FN) area and true negative (TN) area. For LFS problem, TP is the region which is correctly classified as lung, FP is the region where the background is wrongly classified as lung, FN is the region where the lung is wrongly classified as background, and TN is the region which is correctly classified as background. In order to evaluate the segmentation performance of the proposed algorithm, the following metrics are used.

1. *Accuracy*: Accuracy is the ratio of correct predictions to the total number of predictions made by the classifier and can be found using Eq. 14.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (14)$$

Accuracy measure is to be cautiously used while analyzing the quality of a predictive model, as it suffers from accuracy paradox.

2. *Overlap Measure*: It is also known as *Jaccard Similarity Coefficient* and is defined as the ratio of the area of intersection to the area of union in the ground truth image (G) and the segmented image (O), and can be found using Eq. 15.

$$Overlap = \frac{|G \cap O|}{|G \cup O|} = \frac{TP}{TP + FP + FN} \quad (15)$$

3. *Sensitivity* It is also known as true positive rate or recall. It is the probability of correctly classifying a lung pixel and can be computed using Eq. 16.

$$Sensitivity = \frac{TP}{TP + FN} \quad (16)$$

4. *Specificity* It is also known as true negative rate and corresponds to the probability of correctly classifying a background pixel and can be computed using Eq. 17.

$$Specificity = \frac{TN}{TN + FP} \quad (17)$$

4.2 Result of the proposed method

In the proposed method, the lung contour for each image is formed by: (i) performing pixel classification using the trained classifier, and (ii) carrying out iterations of DRLSE with the specific values of the parameters. The kNN classifier used to perform pixel classification gives the probabilistic chance of any pixel belonging to the lung region or the background. These probabilistic chances for all the pixels are converted to binary values by thresholding the probabilities, the threshold value being empirically found to be 0.6, to obtain the segmented output. For pixel classification, the average overlap score of 93.90% is obtained on the testing dataset. However, in some of the test cases, the trained classifier may wrongly classify the pixels near the lung boundary. Therefore, refinement is performed using the DRLSE method.

In the DRLSE method, various parameters need to be optimized before applying it to the test dataset. The parameters of the DRLSE method are empirically optimized and are listed in Table 1. Post-processing step increases the average overlap score to 94.50%. The final output of the proposed algorithm obtained on a few test images is shown in Fig. 5. The proposed method segments most of the images with high accuracy as shown in

Table 1 Parameters used in various modules in the proposed method

Description	Value
<i>Input image</i>	
Size	128 × 128
No. of samples	4096
<i>Classifier</i>	–
Name	kNN
No. of neighbours	15
<i>Post-processing (DRLSE parameters)</i>	
μ , coefficient of distance regularization term	0.2
λ , coefficient of the weighted length term	1
α , coefficient of the weighted area term	0.4
σ , scale parameter in Gaussian kernel	0.8
No. of iterations	25

Fig. 5 Final segmented result of the proposed method after DRLSE step. Row-1 shows input images from the JSRT dataset, Row-2 shows the ground truth labels, and Row-3 shows the segmented output

Fig. 5a–f. However, in few cases due to radiographic artifacts and overlapping anatomical structure the segmentation is not proper, as depicted in Fig. 5g–i. The reasons for improper segmentation are- in Fig. 5g, the lower portion of the left lung is overshadowed by the enlarged heart, Fig. 5h has a bright left clavicle, and Fig. 5i has a darker trachea.

The average overlap and accuracy score obtained on the testing dataset is 94.50% and 98.12%, respectively. Table 2 lists the overlap scores of the proposed method and other LFS methods which have been trained and tested using JSRT dataset. The performance of the graph cut-based method [5] has been computed using the executable code available online [4]. The performance mentioned in the table is the average overlap score obtained when the test set used in our study is given as input to the executable file. As it can be seen from the table, the performance of the proposed method is better as compared to

that of other methods. Moreover, in [20], it has been reported that the *accuracy* of human observer is between 94.6% and 98.4%. Thus, any method that gives a performance in-between these values is considered as robust and can be used for automated LFS. Since, the accuracy of the proposed method is 98.12%, which falls within the accuracy range of the human observer as specified in [20], the method is suited for automatic LFS.

4.3 Computational speed

Segmenting lung fields is only one component of the full CADx pipeline for detection of pulmonary diseases in the CXRs. Thus, the LFS algorithm should operate in real-time and that too with sufficiently high accuracy. The proposed algorithm has been implemented in MATLABTM and executed on a machine with Intel i5 CPU and 8 GB of RAM. The complete execution of the algorithm takes 40.63s for segmenting an image of 128×128 size. Average processing time for each step is also computed. Pixel classification stage takes 31.55s while post-processing took 8.77s. However, comparison of computational speed with other methods has not done as they have been implemented on hardware with different specifications.

Table 2 Performance comparison of the proposed LFS method with other methods

Method	Overlap score
Proposed method	94.50% (Acc: 98.12%, specificity: 98.19%, sensitivity: 97.90%)
SIFT + Graph cut [5]	94.40%
Hybrid ASM-PC [19]	93.40%
ASM optimal feature [20]	92.70%
ASM-SIFT [16]	92.00%
ASM-tuned [19]	90.30%
ASM [19]	87.00%
Ahmad et al. [21]	87.00%
AAM [19]	84.70%
Mean shape [19]	71.30%

5 Conclusion

The paper presented a robust LFS method which is based on the pixel classification method using different statistical and textural features with refinement using the DRLSE method. The algorithm is evaluated on publicly available JSRT dataset containing 247 chest radiographs. The experimental results show the proposed method has an

average accuracy of 98.12% and average overlap score of 94.50%. The experimental results indicate that the performance of the proposed method is better as compared to other shallow-learning based LFS methods.

Compliance with ethical standards

Conflict of interest The authors do not have any conflict of interest.

Ethical statement The research is done following all the ethics guidelines provided by the Springer.

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