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Deep Learning Based Classification of Covid-19 Lung Images

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ABSTRACT

COVID-19 is spreading over the entire world very faster right from the detection of the first case in china during December 2019. In order to identify this viral disease, accurate automatic quantification of the lobes in the lung by means of x-ray and CT. Automated segmentation techniques are needed to overcome the challenges like high variation in abnormal characteristics and low intensity contrast in X-ray and CT slices abnormal and normal tissues. Manual delineation is time consuming and there is a probability of having an intra-observer and inter-observer variability. Hybrid segmentation methods such as FAKM-DRLSE and K-MLRCV methods were proposed to segment the lobes in the lungs. The FAKM clustering method is used to locate the lobes which are further segmented by DRLSE method. In the second proposed method, the edge transformed image obtained from Kirsch operator is provided to the MLRCV method for segmenting the lobes. The segmentation evaluation is done with ground truth images using different evaluation metrics. The segmented images are then given to different classifiers to classify the abnormal images which are COVID infected from the normal healthy images that are non COVID affected. Dense Neural Network (DNN) gives better classification accuracy when compared to all other classifiers.

Keywords: *COVID-19; lung Images; segmentation; classification*

INTRODUCTION

Multiple angles from different X-ray projections are combined to form a Computed Tomography image for detailed cross-sectional areas inside the body. The resulting images are tomographic maps of the X-ray's linear attenuation coefficient. The temporal resolution of basic CT is low in general, but it is improved with multi slice and multi detector techniques which lead to high radiation exposure to the patient.

Segmentation is an important task to quantitatively evaluate function of the lungs. The main challenging tasks of COVID-19 infection detection are the high variation in texture, size and position of infections in CT slices is challenging for detection. The small consolidations of lobes results in the false-negative detection from a whole CT slices Ground Glass Opacities boundaries often have low contrast and blurred appearances, making them difficult to identify as inter-class variance is small.

Acquiring high quality pixel-level annotation of lung infections in CT slices is expensive and time-consuming due to the emergency of COVID19. Hence, there is a need to automate the diagnostic process to improve the sensitivity and accuracy of the test. The goal of this work is to develop hybrid segmentation methods for automatic segmentation of lobes and classify the COVID infected from the normal. Clinicians first roughly locate an infected region during lung infection detection and then accurately extract its contour according to the local appearances like area and boundary which are the key characteristics that distinguish normal tissues from infected ones.

In oreder to delineate lung parenchyma region, vast number of image analysis methods are available in the state of the art. According to Sluimer et al, maximum of these techniques depend on the contrast value which separates the image in to different regions based on the threshold. Threshold method is suitable for normal lung delineation as the contrast of the lungs is different from other regions of the body.

Threshold methods can't delineate the abnormal lung tissues properly when compared to the normal tissues and also the lung vessels. A stepwise segmentation method was given by Hu et al, centroid detection is done by iterative thresholding and then the entire regions are obtained with the help of morphological operations. Wavelet transform also can be used to obtain the initial portions which can be later extended through mathematical morphology operations.

Hybrid methods, Fast Adaptive K-Means with Distance Regularized Level Set Evolution (FAKM-DRLSE) and Kirsch with Modified Local Region based Chan-Vese (K-MLRCV) methods were proposed to segment the lobes. The FAKM clustering method is used to locate the lobes which are further segmented by DRLSE method. In the next proposed method, MLRCV method with distance regularization gets transformed image from the Kirsch operator to segment the lobes. Validation parameters, Dice Metric coefficient and Modified Hausdroff Distance show that the segmentation by K-MLRCV is better than FAKM-DRLSE.

Features of normal and infected lobe regions like geometric, multifractal and intensity features are extracted from the delineation. To increase the rate of classification, feature selection is done using Principal Component Analysis (PCA). The PCA selected features are given to classifiers such as Naïve Bayes (NB), K-Nearest Neighbor (KNN), Support Vector Machine (SVM) and Convolutional Neural Network (CNN) to classify the normal and infected images. Classifier's performance is evaluated with different metrics like sensitivity, specificity, accuracy and F-measure. CNN gives better classification when compared to all other classifiers.

MATERIALS AND METHODS

Existing Method

Edge and region-based are the two main important segmentation techniques that depends on the dissimilarities and similarities between the regions. Threshold is the basic method that divides pixels in to two parts, one having larger pixel intensity values and the other having smaller values than the threshold. Lung lobes segmentation methods available in the art of literature are not so accurate and fail to detect the lobes incase of variations texture and shape. Hence combination of both edge and region based methods such as Hybrid segmentation methods can be proposed.

Level Set, snakes and Dynamic Programming belongs to Edge based segmentation methods. Boundaries can not be delineated properly because of improper lung lesions and energy function minimization. Thresholding, split and merge, clustering, Gaussian-mixture model, probabilistic atlas and graph cut approach comes under Region-based methods. Intensity and texture variations are used to separate the region of interest from the background.

Lung lobes and the lesions are inhomogeneous for CT image and the result overflows which is improper results for the region-based methods. Hybrid segmentation framework that combines boundary-based and region-based techniques methods can be developed for appropriate results of lung lesion segmentation. Clustering with level set hybrid segmentation methods overcomes the limitation of initialization in level set methods by incorporating the centroid from the clustering methods.

The validation of segmentation is vital to know the strengths, limitations and possible applications of a particular algorithm. There are different validation parameters available, like Dice Metric (DM), Jaccard Index (or) Jaccard Similarity coefficient (JI), Hausdroff Distance (HD) and Modified Hausdroff Distance (MHD) to compare the segmented result with the ground truth.

Validation of segmentation algorithm is to understand the strengths, limitations and its potential applications. It speaks about the convergence of the algorithm with the ground truth. Cates et al. (2005) suggested that due to lack of standard metrics and ground truth, segmentation validation is difficult in clinical data. However, in case of biological or clinical data sets, researchers typically rely on experts to delineate the ground truth by hand. Thus hand contouring results are used to assess the performance of a segmentation algorithm. Udupa et al. (2006) stressed the need for an objective evaluation of medical image segmentation on large sets of common clinical data which establishes the validity and clinical applicability of an algorithm. Ge et al. (2007) showed that segmentation performance is generally evaluated either subjectively or objectively by judging several image samples. In contrast, segmentation performance evaluation remains subjective and identifies the correctness of segmentation (Jiang et al. 2006 & Frounchi et al. 2011).

The criteria for validation depend on the purpose of the segmentation procedure such as the quantification of performance based on accuracy, reproducibility or precision and computational time of segmentation methods. Segmentations that are close to the ground truth are considered better than those that are not as defined by the accuracy metrics. The accuracy of an individual experimental segmentation is either given by region overlap which is characterised by a similarity measure or its distance from the ground truth (Igual et al. 2011). Du & Dua (2010) suggested the use of precision, recall and F-score as the traditional quantitative measures in pixel level. These measures are standard techniques that are used to validate the quality of the segmentation results against the ground truth.

Dubuission & Jain (1994) revised HD metric by proposing an improved measure called the MHD, sensitive to small perturbations in point locations for shape alignment. As the difference between the two sets of points increases, its value increases monotonically. Taha & Hanbury (2015) proposed an efficient algorithm with similar performance for sparse and dense points to calculate the accurate HD. Singh et al. (2015) used MHD method with C4.5 classifier and canny edge detection for real face detection.

Feature selection methods select significant features that retain their original physical interpretation based on a criterion function and generate important patterns (Iqbal et al. 2011) for understanding the physical process. In multi-category applications, it is not unusual to encounter problems involving multiple variants of features. Intuitively, it may appear that each feature is useful for discriminations. This large number of features when given as such to a classifier will increase the computational time and interclass variability (Reyes-Aldasoro & Bhalerao 2003). In order to reduce the computational time, it is necessary to select non-correlated features. In general, if the performance obtained with a given set of features is inadequate, it is natural to consider adding new features. There are a variety of methods such as spectrum distribution and wavelet transform for evaluating the performance of the extracted features. Feature reduction and feature selection are used to increase the efficiency of the classifier.

Classifiers are extensively used in discerning abnormal condition from the normal and they play an important role in decision making. Vapnik (1995), proposed Support Vector Machine (SVM) as an effective statistical learning method for classification. The formulation embodies the structural risk minimization principle, which is shown to be superior (Gunn et al. 1997) to traditional empirical risk minimization principle, employed by conventional neural networks. SVMs are found to be advantageous than back propagation neural networks as they have a better efficiency of training, testing and algorithm parameter tuning (Cristianini & Shawe-Taylor 1999, Scholkopf et al. 2000). SVM includes many reliable properties for learning and presents good experimental results; hence, it is used in many application fields (Kulkarni et al. 2004, Chen et al. 2007). SVMs have also been effectively employed in face detection (Osuna et al. 1997), text categorization (Joachims 1997), medical diagnosis (Osarehet al. 2002) and segmentation (Lu et al. 2003). Yang et al. (2007) proposed a feature selection and classification method for hyper spectral images by combining particle swarm optimization algorithm and SVM.

Proposed Method

Image Analysis needs the accurate results of segmentation for object identification or delineation in medical images. As there are various segmentation available in the literature, selection of the more accurate algorithm is important for computerized diagnosis

The CV model is a special case of the Mumford & Shah (1989) problem. Given the curve $c = \partial\omega$, with $\omega \subset \Omega$ being an open subset of the image $I_0(x, y)$ in the image domain Ω, the energy function of the image is minimized as follows

$$\mathrm{F}(\mathrm{c}_1,\mathrm{c}_2,\mathrm{c}) = \mu.\mathrm{length}(\mathrm{c}) + \nu.\mathrm{area}(\mathrm{inside}(\mathrm{c})) + \lambda_1 \int_{inside(c)} \left|I_0(x,y) - c_1\right|^2 dx\,dy + \lambda_2 \int_{outside(c)} \left|I_0(x,y) - c_2\right|^2 dx\,dy$$

- (1)

where the constants μ - Smoothing parameter, ν - Propagation speed and λ_1, λ_2 - Inside and outside driving force. c_1, c_2 are the average intensities that exist inside and outside the contour c and it is represented as

$$c_1 = \frac{\int_\Omega I_0(x) H(\phi(x))\,dx}{\int_\Omega H(\phi(x))\,dx}$$

$$c_2 = \frac{\int_\Omega I_0(x)\left(1 - H(\phi(x))\right)dx}{\int_\Omega \left(1 - H(\phi(x))\right)dx}$$

- (2)

The energy function $\mathrm{F}(\mathrm{c}_1,\mathrm{c}_2,\mathrm{c})$ is minimized with level set function $\phi(x, y)$ as follows

$$\mathrm{F}(c_1,c_2,\phi) = \lambda_1 \int_{inside(c)} \left|I_0(x,y) - c_1\right|^2 H_c(\phi(x,y))\,dx\,dy + \lambda_2 \int_{outside(c)} \left|I_0(x,y) - c_2\right|^2 \left(1 - H_c(\phi(x,y))\right)dx\,dy + \mu \int_\Omega \delta_c(\phi(x,y)) \left|\nabla\phi(x,y)\right| dx\,dy$$

where $H(\phi)$ is the Heaviside function, $\delta(\phi)$ is the Dirac function and ∇ is the gradient operator. In a level set function domain, Heaviside function

$$H(z) = \begin{Bmatrix} 1, Z \geq 0 \\ 0, Z \leq 0 \end{Bmatrix}$$

while Dirac function

$$\delta(z) = \frac{dH(z)}{dz}$$

- (3)

In the proposed automatic Kirsch hybrid method, the weighted average intensities inside and outside the contour at a point p1 is approximated by a neighborhood point p2 where p1 and p2 $\in$ R2 and Ω is a subset of R2 for I original image.

In Kirsch detection method, the kernel masks are obtained by considering a single mask and rotating it in eight compass directions. The final image obtained by the Kirsch operator is I_k and the energy function is rewritten as follows

$$E_k(c_1(p_1), c_2(p_1), c) = \lambda_1 \int_{inside(c)} \left(I_k - c_1(p_1)\right)^2 dp_1 + \lambda_2 \int_{outside(c)} \left(I_k - c_2(p_1)\right)^2 dp_1$$

- (4)

The two constants c_1 and c_2 in CV are replaced by spatially varying functions $c_1(p_1)$ and $c_2(p_1)$ which is given as:

$$c_1(p_1) = \frac{\int_\Omega g_k(p_1 - p_2) I(p_2) H(\phi(p_2))\,dp_2}{\int_\Omega g_k(p_1 - p_2) H(\phi(p_2))\,dp_2}$$

$$c_2(p_1) = \frac{\int_\Omega g_k(p_1 - p_2) I(p_2)\left(1 - H(\phi(p_2))\right)dp_2}{\int_\Omega g_k(p_1 - p_2)\left(1 - H(\phi(p_2))\right)dp_2}$$

- (5)

Where g_k is the Gaussian kernel function and $g_k(p_1 - p_2)$ is the weight allocated to each intensity of $I(p_2)$ at p_2.

In level set methods, an evolving curve c is represented by Lipschitz function ϕ. This is selected such that it is positive inside c and negative outside c. The modified energy function is written as

$$E_k(c_1(p_1), c_2(p_1), \phi) = \lambda_1 \int_\Omega (I_k - c_1(p_1))^2 H(\phi(p_1)) dp_1 + \lambda_2 \int_\Omega (I_k - c_2(p_1))^2 (1 - H(\phi(p_1))) dp_1$$

- (6)

where H is Heaviside function.

Further, the stability of the level set function is preserved by re-initializing it from the degraded shape by introducing a distance regularization term in the level set formulation of Local Region based Chan Vese (LRCV) method. As proposed by Li et al. (2010), the level sets regularization term has both forward and backward diffusion effect, which is defined as:

$$\rho(\phi) = \int \frac{1}{2}(\nabla\phi(p_1) - 1)^2 dp_1 \qquad - \qquad (7)$$

Thus, the minimized energy function is obtained as:

$$E_k(c_1, c_2, \phi) = E_k(c_1(p_1), c_2(p_1), \phi) + \mu R_\rho(\phi)$$

- (8)

The level set regularization term $R_\rho(\phi)$ is defined as:

$$R_\rho(\phi) = \int_\Omega \rho |\nabla\phi| dp_1$$

- (9)

The energy function is minimized by Euler - Lagrange equation to obtain the gradient descent flow as:

$$\frac{\partial\phi(p_1,t)}{\partial t} = \mu div\left[\nabla\phi\left(1 - \frac{1}{\nabla\phi}\right)\right] + \delta(\phi)\left[\lambda_2(I_k - c_2(p_1))^2 - \lambda_1(I_k - c_1(p_1))^2\right]$$

- (10)

where μ , λ_1 and λ_2 are fixed parameters.

RESULTS AND DISCUSSION

The proposed hybrid segmentation algorithms are implemented in MatLab. One of the drawbacks with conventional methods is exact delineation of the lobes. The major challenges in lobe segmentation are its irregular shape, pixel intensity variation, irregular lesions and localization of lobes. The proposed methods FAKM-DRLSE and K-MLRCV are capable of segmenting lung images by combining global and region information.

The original images are clustered using FAKM clustering and the clustered output gives the vector of the mean values of the centroid. The centroid of the lobe which is the region of interest is obtained using connected component labeling based on which the level set function is initialized. The initial contours of lobes are obtained from the clustered output. Lobe detection fails in case of conventional LS method that gives over segmentation output.

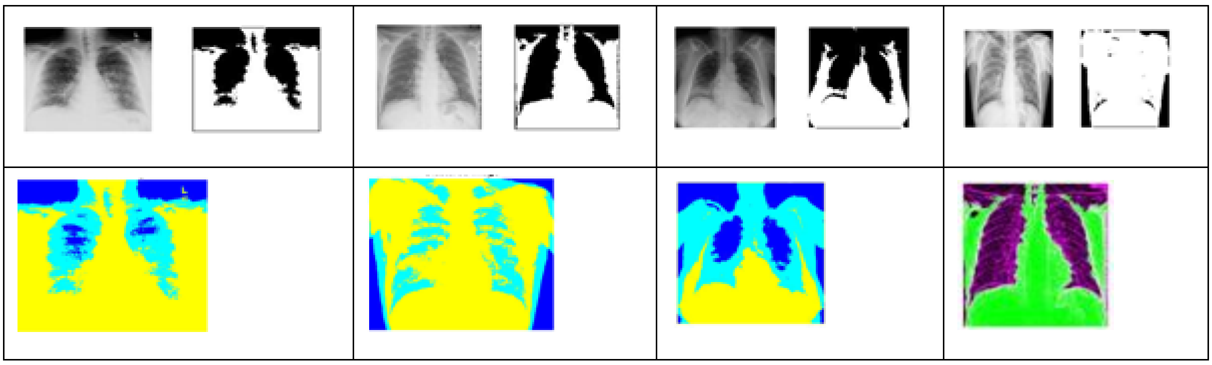

FIGURE 1: Segmentation of chest x-ray images using FAKM-DRLSE method

Clustered output is used for the automatic localization that helps in initialization of level set and its variants for the accurate segmentation of lobes in lung images. The clustering methods are combined with DRLSE to segment both lobes and its results are shown in Figure1.

DRLSE method has different parameters that have to be tuned to obtain better segmentation results. The fixed parameters used in DRLSE method are time step $\Delta t=1$ and the coefficient of the distance regularization term, $\mu= 0.2/\Delta t$. The variable parameters are: Coefficient of the weighted length term, lambda (λ) = 5, coefficient of the weighted area term, alpha (α) = -3, epsilon (ε) = 1.5, specifies the width of the Dirac delta function, sigma (σ) = 0.8, the scaling parameter of the Gaussian kernel. These parameters are varied according to the user assistance based on image acquisition protocol. DRLSE method has the flexibility of evolving two initial contours front and back with the same diffusion at a faster rate. Due to faster rates of diffusion in DRLSE, it gives output with less computational time. However, the problem is with the proper initialization of these contours which is done by the FAKM. So by using FAKM with DRLSE, the lobe portion of lung images is segmented automatically and accurately with less computational time.

In order to consider the challenges of lung CT image segmentation, a new automatic Kirsch hybrid method, combining edge and region-based methods is proposed. There are different variants in the region based active contour methods right from the beginning of CV method such as LCV, LBF, LGAC, LSAC and LRCV. Even though LRCV method can segment left lobe in most of the cases it fails to segment the right lobe. Hence, to improve the performance of segmentation, there is a need for considering the edge gradient information along with region details.

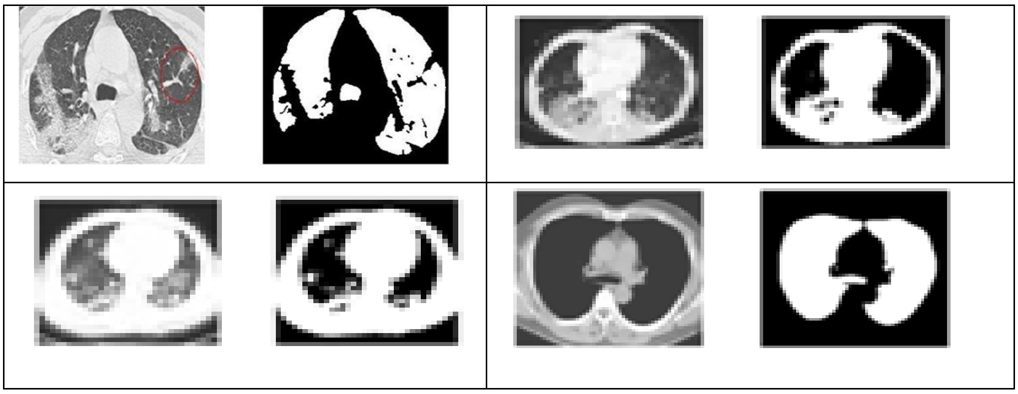

FIGURE 2: Segmentation of lung CT images using K-MLRCV method

The proposed hybrid segmentation method is quantitatively evaluated with the ground truth images based on various similarity metrics like DM, JI, HD and MHD. The DM coefficient measures set of agreements in the image which is given by

$$D(A_a, B_m) = \frac{2|A_a \text{ and } B_m|}{(|A_a| + |B_m|)}$$

Where Aa and Bm are the actual ground truth and manually segmented contours. DM value of 0 indicates no overlap and a value near to 1 indicates a better match between any two different methods. JI coefficient measures similarity and diversity between finite sample sets which is defined as

$$J(A_a, B_m) = \frac{|A_a \cap B_m|}{|A_a \cup B_m|}.$$

The value of the JI varies between 0 and 1. A value near to 1 indicates more similarity between automatic and manual segmentation.

The obtained segmentation results are validated with different validation parameters like Dice Coefficient matrix (DC), Jaccard Index (JI), Hausdroff Distance (HD) and Modified Hausdroff Distance (MHD). Table 1 shows the values of the validation parameters for both proposed hybrid methods. It can be inferred from the values of the table that there is an increase in the values of DC and JI and the higher values of DC and JI nearly equal to 1 indicate higher correlation with the ground truth output. The lower values of HD and MHD after correction indicate higher similarity between the obtained bias corrected segmented output with the manual output.

TABLE 1: Segmentation validation

Parameter → Method ↓	DC	JI	HD	MHD
FAKM-DRLSE	0.72	0.73	3.3512	0.8066
K-MLRCV	0.86	0.95	1.2414	0.1094

Deep learning is a particular kind of machine learning that is composed of multiple processing layers to achieve high levels of abstraction when it comes to learning representations of data. In different domains such as speech recognition and visual object recognition. CNN is a class of deep learning, nowadays supersedes many image segmentation approaches. It is based on multiple layer processing to model high level and complex abstractions in data.

The performance of classifiers such as NB, KNN, SVM and CNN are evaluated with sensitivity, specificity, accuracy and F-measure metrics as shown in Table 3. It is inferred from Table 2 that CNN gives better classification compared to other classifiers.

TABLE 2: Classifier performance measures

Parameter → Classifier ↓	Sensitivity	Specificity	Accuracy	F-measure
NB	0.75	0.73	0.78	0.81
KNN	0.78	0.72	0.71	0.8
SVM	0.89	0.75	0.82	0.87
CNN	0.94	0.85	0.91	0.92

CONCLUSION

FAKM-DRLSE and K-MLRCV are used for lobe segmentation of the lung images. The initialization of the DRLSE method is provided from the clustered output and FAKM gives faster and accurate lobe detection. K-MLRCV method combines kirsch edge detector with MLRCV method. Kirsch edge detector is more efficient compared to various other edge detection methods. In region-based active contour methods, LRCV method gives better segmentation results. Hence, an automatic Kirsch hybrid method is proposed by embedding Kirsch operator for modifying LRCV by regularizing the level set function with a distance regularization term. The classification results show that using a very large number of features combined with a feature selection approach allow us to achieve high classification rates. CNN and SVM training scheme achieves maximum efficiency compared to existing methods.

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