# Survey on Lung Segmentation in Chest X-Ray Images

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***Abstract*— Computer aided techniques play vital role in medical image analysis. In olden days every field of medical diagnosis take more time to analyse and identify the diseases. Most of the time it leads to failure in correctly and timely identification of patient condition, particularly Lung cancer needs more support from Computer aided techniques. Early detection of Lung cancer increases the life time of human beings. Advancement of medical field introduces lot of techniques to observe patient condition such as chest X-ray image, Computer Tomography images, Magnetic resonance and Sputum Cytology. To develop an intelligent system through understanding of the existing techniques in the literature is essential. Initial need is to segment the lung portion in the X-ray image. This paper presents the survey on the existing segmentation techniques in the literature and its advantages and disadvantages with the intention to find out the place for improvement that helps the diagnosis in an improved manner.**

***Keywords*: Segmentation, Morphological, Machine learning, Threshold**

## I. INTRODUCTION

More than decade's lung cancer creates drastic loss in human survival [1]. It requires early and timely detection of disease and it is a several stage process for radiologists to detect lung cancer accurately. Computer aided techniques and Computer Aided Diagnosis (CAD) are gifts of computer era which reduces complications in medical image diagnosis. Advancement of CAD techniques like convolution neural network, Deep Neural Network, Auto encoders gives more provision for medical image analysis. In our body chest bone locks most organs and extraction of each organ from one another is a difficult process for radiologist. Chest X-ray image needs emerging assistance from CAD techniques for analyzing and identification of lung cancer. Normally Lung segmentation and Nodule detection done with the help of computer aided detection system with nodule segmentation and nodule diagnosis is carried out with CAD system. Lung segmentation is the root for all other process of cancer identification and detection in chest X-ray images. Based on proper accuracy and sensitivity of lung segmentation, lung cancer detection and diagnosis results in early treatment for patients and help to increase the life time of cancerous patients. The result of X-Ray images are always result poor in quality, It needs a lot of improvement over the lung image, this can be done with the help of preprocessing techniques Like enhancement, noise removal and filters. Accurate segmentation of chest X-ray image is difficult and time consuming process. Image enhancement little bit improves the image quality but segmentation needs more attention. The type of image and purpose of segmentation decides techniques being used by the researchers. Now a days machine learning algorithms plays vital role in lung image segmentation.

The aim of this paper is to present the novel techniques in image processing used by various researchers. In this paper survey regarding various up-to-date techniques available in chest X-ray lung segmentation is presented. An original research out line for the related research work for lung segmentation in chest X-ray images is given. It also discusses various techniques being used in digital image processing. The main organization in this survey is a classification of various image processing techniques in lung segmentation. The reminder of this paper organized as follows: Section 2 overviews the application of image processing in medical image analysis, Section 3 discusses threshold based segmentation, Section 4 summarizes the edge and morphological based methods, Section 5 provides the region based segmentation, Section 6 highlights the machine learning based segmentation, Section 7 concludes the paper with scope of further exploration.

## II. MEDICAL IMAGE ANALYSIS

In medical image segmentation image processing plays a prominent role. Vanita Naronha et al. summarized the causes of lung cancer and its status of human survival particularly in India and also state about stages of lung cancer and its therapy and also pointed about importance of CAD techniques in Lung cancer diagnosis [1]. Senthilkumar et al. tried different enhancement techniques like histogram equalization, adequate histogram equalization and CLAHE. These techniques are experimented in chest X-ray images and estimated that CLAHE has given best result than other two[2]. Pierre Gravel at al. examined intensity variance improved by minimum curvature filtering and enhanced the image by wavelet filtering. Created high resolution images with the help of dual energy imaging integrated with restoration process[3]. Aroop Mukherjee et al. used binarization method to enhance the image resolution with the combination of binarization and threshold and also presented algorithms to execute it and enhanced the image [4]. AsmaYasrib et al. analyzed the importance of image processing in image retrieval. Content based image retrieval is used instead of manual annotation of medical images, also pointed shape queries using image and VHD-MMS, artificial neural network is also used for medical image retrieval. In medical field, image processing is used for diagnosis and research, various techniques are used to enhance the image and restoration and comparison [5]. Preeyanan Pattrapisetwong et al. examined images from JSRT dataset and resized for further processing and adjusted the contrast, second outline of the lung is enhanced with the help of shadow filter, third lung is segmented with the help of local thresholding and removed unwanted regions and finally noise are eliminated by morphological operations and edge refinement techniques. Performance accuracy is measured by overlap, accuracy, sensitivity, specificity, precision, and f-score and achieves 97.28% in accuracy and 91.36% in overlap [6]. Preeti Aggarwal et al. discussed about segmentation problems in lung CT(Computed Tomography) and thyroid US(Ultra sound) and automated tools like MaZda, YaDiv and MATITK are used to segment lung CT images. Algorithms are created to execute automatic lung segmentation to avoid manual threshold. Justin Ker et al. reviewed about application and challenges of machine learning algorithms in medical image analysis which includes available types of medical imaging and supervised learning models, convolution neural network, recurrent neural network and unsupervised learning models, auto encoders, restricted Boltzmann machines, deep belief net-works and generative adversarial networks and used machine learning in classification, detection, localization, segmentation and registration [8]. Erik Smistada et al. has concluded that graphical processing unit(GPU) plays an important role in increasing machine processing speed, so for medical image analysis support of GPU is very important in segmentation, registration, denoising, filtering, interpolation and visualizing. Working methodology and features that affect the performance of GPU is also explained with the help of data parallelism, thread count, branch divergence, memory usage, synchronization. Normally algorithms gives best result if the GPU has process data parallel, more threads, absence of divergent branches, minimum memory usage and less synchronization. The factors like GPU optimization, grouping, texture, constant and shared memory and stream compaction also affect the performance of GPU. They also discussed segmentation methods thresholding, region segmentation, morphology, watershed, active contour, level sets, atlas / registration based, intensity registration based, feature based registration, statistical shape models, markov random fields and graph cuts, centerline extraction and segmentation of tubular structures, kalman filter in terms of GPU. Finally they recorded GPU works well and suitable for segmentation in contour. Statistically important points are considered where points more than thousands, Iterative process in 3D images are problematic, branch divergence reduces the performance of region growing and narrow-band level sets. The importance of GPU utilization and its hardware and software predictions are also discussed in this paper [9].

## III. THRESHOLD BASED SEGMENTATION

Threshold is a basic pillar of segmentation. Threshold based segmentation is a gift for initial researchers. It simply separates foreground and background. Threshold based segmentation plays an important role in medical image segmentation. It works on the concept of pixel value in image compared with predefined value of threshold. Nobuyuki Otsu et al. pointed that automatic threshold is selected based on gray levels. Consider only zeroth and first order cumulative moments of histogram gray levels and successfully created automatic threshold selection and multilevel threshold [10]. Senthilkumaran et al. modeled best thresholding algorithm for basic Segmentation of lung region and also compared the results with niblack and sauvola local thresholding algorithms. Accuracy of segmented lung image calculated with the help o f jaccard similarity coefficient method and PSNR [11].Vijay Jumb et al. examined HSV based segmentation using k-means clustering and used OTSU threshold to get suitable threshold value for image segmentation. The proposed algorithm was compared with 3 algorithms region Growing (RG), Fuzzy C-Means clustering (FCM ), climbing with k-means (HKM) and PSNR and MSE values are used to compared all the results[12]. Liu Jianzhuang et al. developed two- dimensional Otsu method and compared this proposed method with previous one dimensional Otsu method. Experimental results revealed that 2-dimentional Otsu method works better than one dimensional Otsu method [13]. QuocBao Truong et al. developed automatic multilevel threshold with the support of improved Otsu method by evolutionary approach. Automatic thresholding algorithms developed based on adaptive genetic algorithm and hill climbing algorithm and record proposed method achieve segmentation with lowest time[14].Yu Liu et al. used Otsu method to segment in the image which works on the basis of gray extension [15]. Reddi et al. developed both single and multilevel threshold algorithms and also implemented these algorithms with some samples [16]. Orlando Tobias et al. proposed histogram based threshold to segment the image which works on the concept of gray level similarity and this information is evaluated with the support of fuzzy measure [17]. Thamilarasi et al. developed perfect segmentation algorithm for chest X-ray images based on canny with morphology and threshold. Basic enhancement with these algorithms are executed in all 247 images and compared accuracy of results with the help of jaccard similarity coefficient method and pointed threshold based
method gives 80% success rate in lung segmentation than canny with morphology method[18]. Thamilarasi et al. produced new method for automatic thresholding of segmentation of lungs which is done with the help of mean and standard deviation based on green channel in chest X-ray lung image. Basic enhancement is carried out with median filter and histogram equalization techniques and also developed three algorithms based on mean and standard deviation which is implemented in RGB channels. Green channel gives better result than red and blue channels. This experiment JSRT dataset is taken and tested before and after filter application in image . Otsu, niblack and sauvola automatic thresholding algorithms are also tested with these images. All these results are compared with the help of dice coefficient similarity method [19].Dawoud et al. examined statistical features of lungs based on size, orientation, major and minor ellipse lengths, eccentricity and centroid locations and manually segmented by radiologist. Test images are segmented by iterative thresholding, finally both method similarity are compared with the help of mahalanobis distance then result of contour segmentation is adjusted using active shape model (ASM)[20].

## IV. EDGE AND MORPHOLOGICAL BASED METHOD

It is simple and most adaptable method for boundary detection and execution based on the concept of identifying location of pixels in an image. It gives the object or image edge without any loss of minute details. Muthukrishnan et al. discussed edge based segmentation as basic tool for image segmentation. Edge processing of image reduces the remaining process of image segmentation; it provides the absolute details of image like shape of object. There is a lot of edge detection techniques available like robert , sobel, prewitt , kirsch, robinson , marr-hildreth , LoG , and canny edge detection. Based on the type of image and requirement these techniques produce different results[21]. ZhaoYu-qian et al. pointed different noise removal techniques likesalt and pepper and edge detectors like laplacian of gaussian operator, sobel operator and mathematical morphological operations like dilation, erosion, opening, closing with different structuring elements and compared the results of above operator and concluded mathematical morphological operation is suitable for edge detection. All these experiments are implemented with CT lung images[22]. Ravia Shabnam Parveen et al. presented lung boundary detection. It is executed with three steps , first input X-ray image similarity is measured with the support of Content Based Image Retrieval(CBIR), second Scale-Invariant Feature Transform(SIFT) flow non regid registration is used to extract features by few steps and finally segmentation is done with graph cut algorithm. Similarity is compared by jaccard similarity coefficient, dice's coefficient and average contour distance [23]. Sema candemir et al. examined different chest X- ray database sets of lungs and detect the lung boundaries using SIFT-Flow Non-Rigid Registration for feature extraction. Graph cut algorithm is used for segmentation and fast partial random profile for similarity selection. Compared the results and predicted the success rate of datasets [24]. Akhila et al. formulated content-based image retrieval method to identify training images and images from JSRT and other 2 datasets are taken, totally 585 chest radiographs used for experimental analysis. Lung shape is created using SIFT-flow and image similarity is optimized with non regid image registration and segmentation by graph cut optimization method. Finally achieved highest accuracy of 95.4%[25].

Matthew Browna et al. predicted two approaches for segmentation. Knowledge based architecture combines three aspects such as knowledge based model, image processing routines, an inference engine and blackboard for communication. Segmentation is based on both normal and abnormal feature values. The system extracted and matched the edges of image and derived some common feature values from image and modeled objects based on those features and compared based on those common features. Symbolic description is created with the help of matched edges. Finally analyzed and reported the abnormalities. Symbolic features are converted to natural language with the help of high level rules.

For each anatomical structure the system follows name, shape, structural relationship and characteristics of image. Costel edge, hemi diaphragms, mediastinal surfaces and lung apices edges of chest X-ray are recorded. Model shape is used to describe relation between these features edges and shape. Parameters in upper and lower bound consider features of strength, orientation, position and length for all these edges and shapes. Segmentation is done based on priori and posteriori anatomical structure. After the segmentation, knowledge based constraints get from blackboard and passed to image processing engine. Finally extracted edges matched to the anatomical structure. Canny edge detection is used with multiple resolutions to detect the edges. Inference engine is used for decision making and fuzzy set is used to describe its feature values and used for testing to find abnormalities [26].

Tao Xua et al. proposed Active Shape Model (ASM) for automatic lung field extraction in normal and abnormal images and achieved 3-4% improvement in accuracy, sensitivity, specificity. In old method ASM needs three steps, shape learning stage, shape model generation and segmentation. In shape learning stage Gray level pattern of image is statistically analyzed the training image dataset and this is executed by shape model generation and Gray Level Appearance Model (GLAM) generation and initialization stage, the shape contour is created. After contour initialization, segmentation is done with shape model and GLAM model and these steps are repeated until get final segmentation. This method used global Edge and Region Force (ERF) field based ASM (ERF-ASM) for lung field segmentation and lung filed shapes learnt with the help of Principal Component Analysis (PCA). It is executed with three methods , shape initialization done with global edge and region information, second new point evaluation technique for locating target contour field and remove the restriction of initial landmark points appropriately close to the target contour. Finally, the limitation of manually adjusting position parameters is eliminated.

Automatic initialization stage includes estimation of energy, select isomodel of estimated energy, optimal edge and region map generation, ERF field calculation finally carried out segmentation. Final results are compared with old ASM and Level-Set with Shape Priors (LSSP) method and recorded proposed method works better than typical ASM[27].

Jeff Duryea et al. proposed the algorithm to get right and left lung separately with the support of filter wheel equalization system. It is used to detect the size, shape, position of lung fields. The images are resized and created hand tracing from human observer. This algorithm worked based on several parameters. First contrast of the image is enhanced and identified the edges and select center point from each group. It would remove wrongly classified pixels and find lower and upper edges. It also removed non anatomically shaped pixel and isolated pixel. Finally got segmented portion of the image [28].

## V. REGION BASED SEGMENTATION

Region based segmentation partition the image based on color, shape, intensity and texture into similar areas of connected pixel, each pixel in the region have same characteristic of that region. Xuechen Li et al. has improved the lung segmentation with statistical and appearance models and used JSRT dataset and attained high accuracy overlap of 93.1%. Active appearance model is used to describe statistical feature of the lung border and these results are compared with training set. Statistical shape model and statistical appearance model are used to get statistical features and model evaluated with mahalanobis distance, smallest value of mahalanobis distance is taken for better position. Initial positions are set by gray level intensity values, normalized by self-adaptive stretch method. Accuracy of proposed segmentation method is evaluated by dice's coefficient (DSC), sensitivity (SEN), specificity (SPE), accuracy (ACC) and overlap (OVL) and results in DSC one case above 0.9, SEN 98% cases above 0.9, SPE and ACC one case above 0.95%, OVL 93.5% cases above 0.9 and all cases above 0.85. The results of the proposed method are compared with previous ASM method by average, standard deviation, maximum and minimum. It produced best result in automatic lung segmentation by statistical shape and appearance models [29].

Hui Luo et al. proposed a new object oriented knowledge based model for lung region identification and segmentation. Object oriented knowledge model shows the relationship between data and actions which include the properties of Object Oriented Programming (OOP) abstraction, encapsulation, information hiding, inheritance and polymorphism. So this model mostly suitable for image analysis knowledge model.

Model class attributes are used to describe model features, so it is observed that common features from Image are extracted as description attributes, composition attributes and semantic relations. Description attributes give the relationship between model and its instances by using its features size, shape, color, texture, position and orientation. Similarity of complex anatomical structure components are identified by hierarchy representation of image type and its component objects. Semantic graph attribute shows the relationship between same level component objects and adjacency components ( left and right).

Model class models represent the relationship between images and its model is based on scheduling strategy and matching mechanism. Scheduling strategy is used to reduce the complexity in dividing complex structure and minimize the time. Matching algorithm is used to locate the image objects and verify the patterns.

Design of chest anatomical model explains the textural characteristics, spatial characteristics, and shape characteristics of lung image. Lung region is easily identified by using the body model match, the spine model match and the lung model match.

In body model entropy thresholding is used to compute threshold and noise is removed with the help of opening operation. Finally binarized image of body model is matched to the binary chest image. Boundary of spine column is detected by automatic spine boundary detection algorithm. Based on boundary point initial contour of lung is created and perfect lung region is segmented with the help of snake model. This approach gives similarity as 80% result in medical image database [30]. Kesav Kancherla et al. discussed nucleus feature based lung cancer detection in Biomoda dataset. Selected 71 shape, intensity and color related features with nucleus segmented features and achieved the accuracy of 87%. The nucleus segmentation is done with the help of seeded region growing segmentation method.

The biomoda dataset based on sputum samples are taken. First samples are collected from patients and processed with ultraviolet microscope with FITC filter, slide scoring and analyzing is done with cypath slide scoring procedure. Segmentation is performed with thresholding technique and initial set feature are selected based on shape, intensity, color. Average Intensity, minimum intensity, variance, mode, maximum intensity, skewness and kurtosis features are taken for intensity and aspect ratio, size of the cell and circularity of the cell for shape related features. Wavelet transform is used for texture based features and it also captured shape related features.

Nucleus based segmentation is done with region growing method. First, the image is enhanced with median filter, histogram equalization and top hat transformation. Second seed point selection is based on florescent and maximum florescent value is taken for seed value. Third threshold calculation is based on th1 and th2. Th1 takes maximum difference between average and pixels surrounded by 5x5 pixel block. For Th2 is calculated using gradient of 5x5 blocks centered at initial seed and fixed average as threshold. Threshold value is changeable based on its nucleus size. Combination of current set of seeds and newly added seed give the current seed. It satisfies the condition if average <= th1 and <=th2[31].

Paola Campadelli et al. has used JSRT dataset for segmentation, the size of image is reduced to reduce the processing time. To identify vertical axis and the lung borders two edge detection techniques are used, First Gaussian filter at different orientation and laplacian of Gaussian at three different scales. Result of these methods gives lung border with identifiable contour and applied these segmentation algorithms in both JSRT and 162 radiographs from Niguarda Hospital. To enhance the nodule at different sizes and brightness by Gaussian filter standard deviation takes range between 2-12 based on minimum and maximum size of nodule radius. Subtracting nodule subimage with smoothen version will be resulted in positive values at peak and negative values in neighborhood. Created binary image by selecting peak values and summing all binary images at different scales and obtain final image. The resulting sum image contains circle shapes and is surrounded by a darker ring. All regions appearing only one of the binary images are taken as candidates, after this extraction average of 130 regions per image were obtained. For each region 41 features studied and selected 21 features as top based on statistical analysis and 7 features selected for extraction. Finally lung is segmented [32].

Yonghong Shi et al. proposed new deformal model for patient specific shape statistics and population based statistics to segment the lung field from serial chest radiographs. SIFT used to get features and extract deformal contour for both statistics there by produced higher accuracy in segmentation. The population based shape statistics is used to force the deformal contour, patient specific shape collected from online and every time results are modified based on recent updates. The proposed active shape model gives robust and better result than previous models[33].

Bram van Ginneken et al. tried automatic detection of lung fields executed with combination of hybrid methods. The methods used are a matching approach, pixel classifier, rules based scheme, hybrid scheme and the results are compared and with inter observer variability and found hybrid scheme with combination of rule based segmentation and pixel classifier gives more accuracy. Totally 115 images are tested and attained the accuracy of 94%. First segmented image is matched with input image , second rule based contour detection after identifying border its overlap with edges and ridges and this overlapping is avoided by using dimensionality reduction technique and detect the rib cage, mediastinum, edges diaphragm and lung tops. The segmentation is followed by detection of lung center lines, detection of right / left lungs, detection of right/ left rib cage, detection of diaphragm, detection of lung tops, pixel classification, pixel classification in intensity and location, rule based reasoning in intensity and corrected location, rule based reasoning in intensity and entropy and corrected location, rule based reasoning and correction using pixel classification. Finally calculated accuracy, specificity and sensitivity for both lung and background and found rule based reasoning with hybrid scheme gives good result [34].

Mercy Theresa et al. used watershed algorithm for segmentation of lung images in chest X- ray radiographs and feature extraction is done by using five different transforms and it is implemented for all 247 images in JSRT database. The result of this method is examined using various statistical features like energy, entropy, mean and median [35].

## VI. MACHINE LEARNING IN LUNG SEGMENTATION

Machine learning techniques play major role in fast and accurate segmentation of lung images which also produces higher accuracy than traditional segmentation methods. Deep learning techniques are milestones in medical image segmentation, which produce maximum results with high accuracy.

Osamu Tsujii et al. examined 1-D convolutional neural network as follows. First the image is shrunken and secondly the image is resolved to horizontal and vertical direction and both directions trained with neural network. From the output of neural network two dimensional image is reconstructed and binarization and labelling is done individually. Finally two post processed image combined through OR operation and labeling to get final contour. The proposed method gets 94% accuracy for test images and also implemented in training images [37].

Sergii Stirenko et al. examined deep CNN processed for segmentation, data augmentation, dataset stratification and exclusion of non-evident outliers and gave best result in bigger, small and not well balanced dataset. Lung segmentation is done with both lossless and lossy data augmentation. First Shenzhen Hospital (SH) dataset is taken for lung segmentation which is not well balanced and cut left and right lungs from CXRs and prepared masks and named as segmented SH dataset. Comparison of training and validation result is show over fitting in small size of data decreased by data augmentation methods. This is the reason to use both lossless and lossy types of data augmentation.

For 2D images lossless data augmentation is included in mirror like reflections and rotation by 90n degrees, the value of n is n=1,2 and 3. It increases the reliability, efficiency and accuracy during training and validation [38].

Rahib Abiyev et al. presented the detection of lung diseases like Tuber Culosis (TB), pneumonia and lung cancer in chest X-ray images with the help of machine learning algorithms like back propagation neural network, competitive neural network, convolutional layer, subsampling layer and also developed simulation for these algorithms to implement chest X-ray images for disease detection and compared the results of CPNN and BPNN. BPNN achieves high success rate of 99.19% than CPNN (89.57%). Finally they recorded proposed CNN gives the best result [39].

Akira Hasegawa et al. modeled shift-invariant convolutional neural network to detect lungs from chest radiograph and create novel algorithm to smooth the lung boundaries. Followed three steps to achieve this result, First in preprocessing, the size of image is reduced and enhanced by histogram equalization. Second the images are trained by neural network. Third the boundaries are extracted by adaptive thresholding and noises are removed with laplacian filter. Finally the eroded boundary is smoothened by change of tangent in each pixel boundary[40].

Yu. Gordienko et al. examined segmentation of 2CXR lung images and used bone exclusion technique with the support of deep learning techniques and identify the cancer portion in lung image. They used Japanese Society of Radiological Technology (JSRT) dataset and Bone Shadow Elimiated (BSE)-JSRT dataset without clavicle and rip bone. First bone elimination is

done in JSRT and BSE-JSRT. Secondly left and right lung are extracted with the support of U- net(Fully Convolutional Network) based convolutional neural network. In CNN only 7 convolution 2D layers are used for original, bone eliminated, segmented datasets JSRT and BSE-JSRT. Then segmentation is done with Miller & Charles (MC) dataset by manually prepared mask and predicting lung borders with the help of trained U-net based CNN from JSRT #01 and BSE-JSRT #02 dataset. Finally CNN was trained with GPU mode with original JSRT#01 and BSE-JSRT#02 dataset and segmented JSRT#03 and BSE-JSRT#04 dataset. Training and validation of results shows high accuracy and low loss.

Graphical representation of training accuracy, validation accuracy, training loss, validation loss for the images without bone, the segmented image and the segmented image without bones also recorded. The image size 1024×1024 for chest X-ray dataset and 2048×2048 for JSRT dataset and reported this method of segmentation using deep learning gives better result than others [41].

Tuan Anh Ngo etal.used hybrid method with the combination of distance regularized level set and deep structured inference. JSRT dataset is used and achieve accuracy 94.8% to 98.5%.Jaccard Similarity Coefficient (JSC), dice's coefficient (DSC), and average contour distances (ACD) are used to measure the accuracy of segmentation [42].

## VII. CONCLUSION

Every year causes of lung cancer in human life plays challenging role in medical field. Early Cancer identification needs immediate support from technology. CAD techniques are rainbow of digital image processing. It scatters miracles in every aspect of medical image segmentation and produce effective result by producing early recognition of lung cancers. Table 1 shows the result of few experiments in lung segmentation. Lung segmentation is important for cancer identification. High accuracy in segmentation gives the best result in lung cancer detection. In this survey lung segmentation experiments performed by various researchers are focused. Different segmentation techniques available in digital image processing which are more useful for medical image analysis, segmentation and cancer detection are also reported.

TABLE 1

METHODS AND ACCURACY REPORTED BY VARIOUS RESEARCHERS

| Aurthors | Data set | Methods | Accuracy | Similarity |
|---|---|---|---|---|
| PreeyananPattr apisetwong et. al | JSRT | Shadow Filter, Local Thresholding, Morphological operations. | 97.28% in accuracy & 91.3% in overlap | - |
| JohnatanCarva lhoSouza, et.al | MC | AlexNet deep convolutional network (CNN), Res Net18 CNN. | - | |
| N.RaviaShabnam Parveen | - | CBIR, SIFT flow non regid registration, graph cut algorithm | - | - |
| K.J. Akhila, et. al. | JSRT | CBIR, Bhattacharya shape similarity measure and Radon transform measure, SIFT flow non regid registration, graphcut optimization algorithm | 95.4% | - |
| Dawoud, et. al | Publically available data set. | Statistical features, iterative thresholding, Active Shape Model. | - | Mahalano bis distance |
| V.Thamilarasi, et al | JSRT | Median Filter, Histogram Equalization, Mean and Standard Deviation calculation, RGB channel. | High | Dice Similarity |
| SergiiStirenko,et,al | SH | Deep CNN, | High | - |
| Mohammad Hesam Hesamian, et al | Not mentioned | CNN, 2D CNN, 2.5D CNN, 3D CNN | Big Organs - 0.937 | Dice Similarity |

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