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Cancer Detection through CT scan Images Using Gabor Filter Method and Classification Using Pnn

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ABSTRACT

In this project, a novel method of detecting the lung cancer including the size of the cancer acquired tissues. They are slow and often unreliable. In an effort to reduce the burden of the disease, this project gives an automated approach for diagnosing lung related diseases. We first extract the lung region using a graph cut segmentation method. For this lung region, we compute a set of texture and shape features, which enable the CT scans to be classified as normal or abnormal using a PNN classifier. In addition to the detection, classification is done using the PNN based artificial neural network. Hence, a large data base of lung images can be easily classified. Even noisy images could be considered with a variance of less of than 0.0001 is taken into account. The performance analysis has been presented with our method and various existing methods. An accuracy of 99% had been obtained while PNN classifier based supervised learning is used. In addition to accuracy, time comparison was performed with earlier methods, such as C means, and SVM based classification methods. Even the time of cancer detection and time of classification is better in our proposed work and it works out to only 20% of other algorithms such as SVM. This type of novel method helps in the fastest diagnosis and helps in early treatment and reduces the death rate of human because of lung cancer. The project is simulated and implemented in mat lab version 7.13 using image processing toolbox and the images were obtained from online open source biomedical image vendors.

INTRODUCTION

Lung cancer, also known as carcinoma of the lung or pulmonary carcinoma, is a malignant lung tumor characterized by uncontrolled cell growth in tissues of the lung. If left untreated, this growth can spread beyond the lung by process of metastasis into nearby tissue or other parts of the body. Most cancers that start in the lung, known as primary lung cancers, are carcinomas that derive from epithelial cells. The main primary types are small-cell lung carcinoma (SCLC) and non-small-cell lung carcinoma (NSCLC). The most common symptoms are coughing (including coughing up blood), weight loss, shortness of breath, and chest pains.The vast majority (80–90%) of cases of lung cancer are due to long-term exposure to tobacco smoke.About 10–15% of cases occur in people who have never smoked. These cases are often caused by a combination of genetic factors and exposure

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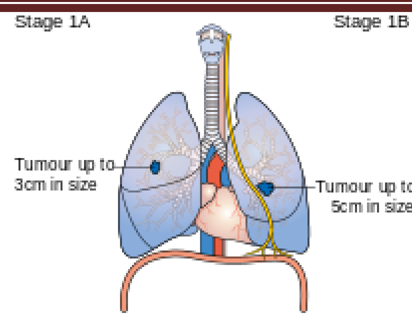
to radon gas, asbestos or other forms of air pollution, including second-hand smoke. Lung cancer may be seen on chest radiographs and computed tomography (CT) scans. The diagnosis is confirmed by biopsy which is usually performed by bronchoscopy or CT-guidance.

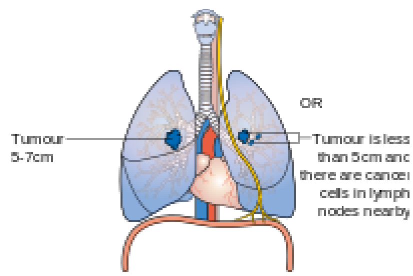
Signs and symptoms

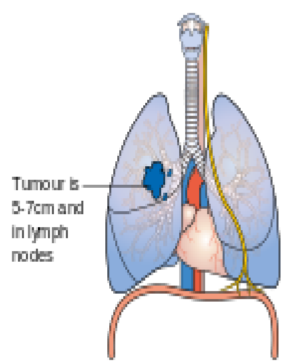
Signs and symptoms which may suggest lung cancer include Respiratory symptoms: coughing, coughing up blood, wheezing or shortness of breath Systemic symptoms: weight loss, fever, clubbing of the fingernails, or fatigue Symptoms due to the cancer mass pressing on adjacent structures: chest pain, bone pain, superior vena cava obstruction, difficulty swallowing If the cancer grows in the airways, it may obstruct airflow, causing breathing difficulties. The obstruction can lead to accumulation of secretions behind the blockage, and predispose to pneumonia.

Diagnosis

Performing a chest radiograph is one of the first investigative steps if a person reports symptoms that may suggest lung cancer. This may reveal an obvious mass, widening of the mediastinum (suggestive of spread to lymph nodes there), atelectasis (collapse), consolidation (pneumonia) or pleural effusion. CT imaging is typically used to provide more information about the type and extent of disease. Bronchoscopy or CT-guided biopsy is often used to sample the tumor for histopathology.







LITERATURE SURVEY

Most of the researchers develop many methods to diagnose lung cancer. An expert system is designed to diagnose the heart disease and is based on fuzzy logic it uses the dataset of V.A. Medical center. All the symptoms are considered and membership function is calculated for both input and the output variable. Finally a rule base is created

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and rules are fired based on the symptoms for the patient.

This system provides information only about the disease and not about stage and treatment. [3] A fuzzy expert system is developed to determine coronary heart disease risk of patients and gives the user the ratio of the risk for normal life, diet and drug treatment [4]. A Fuzzy rule based lung disease diagnostic system combining the positive and negative knowledge was developed using contexts, facts, rules, modules and strategies of knowledge representation to identify medical entities and relationship between them for diagnosis of lung cancer[5]. An Intelligent system for Lung cancer diagnosis is designed that detects all possible lung nodules from chest radiographs using image processing techniques and feed forward neural networks. It classifies the nodules into cancerous and non-cancerous nodules [6] numerous applications implement computer-assisted evidence-based lung cancer diagnosis by utilizing of Tomosynthesis. It offers high shadow detection sensitivity at a low exposure dose which recreates multi sectional images from a single scan and offers image processing to produce artifacts [7]. In PET/CT Images the exact position of boundary of the tumor was manually identified, five optimal threshold features and two gray level threshold features of the tumors were extracted from the B-mode ultrasonic images, an optimal feature vector was obtained using K-means cluster algorithm and a back propagation artificial neural network, was applied to classify lung tumors [8].Dynamic tumor-tracking treats the lung as an elastic object and analyzes the deformation based on linear Finite Element Method. The doctor planning the radiotherapy can reproduce the movement of the lung tumor by freely adjusting the regions, displacements, and phases of the boundary conditions while comparing the position of the lung tumor in an X-ray photograph [9].

EXISTING METHODS- THRESHOLDING

In existing paper, the author represents Lung Cancer Detection System for finding of lung cancer by analyzing chest X-rays with the help of image processing mechanisms. This system assists to radiologists for their X-ray image interpretation of lung cancer. This paper presents a neural network based approach to detect lung cancer from raw chest X-ray images. The author use an image processing techniques to denoise, to enhance, for segmentation and edge detection in the X-ray image to extract the area, perimeter and shape of nodule. These extracted features are considered as the inputs of neural network to train and to verify whether the extracted nodule is a malignant or non-malignant. This research work concentrate on detecting nodules, early stages of cancer diseases, appearing in patient's lungs. Most of the nodules can be observed after carefully selection of parameters. The training dataset of X-ray images are processed in three stages to attain more quality and accuracy in the processed examination. Thresholding is the simplest method of image segmentation. From a grayscale image, thresholding can be used to create binary images.

THRESHOLDING METHOD

During the thresholding process, individual pixels in an image are marked as "object" pixels if their value is greater than

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some threshold value (assuming an object to be brighter than the background) and as "background" pixels otherwise. This convention is known as threshold above. Variants include threshold below, which is opposite of threshold above; threshold inside, where a pixel is labeled "object" if its value is between two thresholds; and threshold outside, which is the opposite of threshold inside (Shapiro, et al. 2001:83). Typically, an object pixel is given a value of "1" while a background pixel is given a value of "0." Finally, a binary image is created by coloring each pixel white or black, depending on a pixel's label.

Threshold selection

The key parameter in the thresholding process is the choice of the threshold value (or values, as mentioned earlier). Several different methods for choosing a threshold exist; users can manually choose a threshold value, or a thresholding algorithm can compute a value automatically, which is known as automatic thresholding (Shapiro, et al. 2001:83). A simple method would be to choose the mean or median value, the rationale being that if the object pixels are brighter than the background, they should also be brighter than the average. In a noiseless image with uniform background and object values, the mean or median will work well as the threshold, however, this will generally not be the case. A more sophisticated approach might be to create a histogram of the image pixel intensities and use the valley point as the threshold. The histogram approach assumes that there is some average value for the background and object pixels, but that the actual pixel values have some variation around these average values. However, this may be computationally expensive, and image histograms may not have clearly defined valley points, often making the selection of an accurate threshold difficult. One method that is relatively simple, does not require much specific knowledge of the image, and is robust against image noise, is the following iterative method:

1. An initial threshold (T) is chosen; this can be done randomly or according to any other method desired.
2. The image is segmented into object and background pixels as described above, creating two sets:
   1. $G_1 = \{f(m, n):f(m, n)>T\}$ (object pixels)
   2. $G_2 = \{f(m, n):f(m, n)T\}$ (background pixels) (note, $f(m, n)$ is the value of the pixel located in the m^{th} column, n^{th} row)
3. The average of each set is computed.
   1. m_1 = average value of G_1
   2. m_2 = average value of G_2
4. A new threshold is created that is the average of m_1 and m_2
   1. $T' = (m_1 + m_2)/2$
5. Go back to step two, now using the new threshold computed in step four, keep repeating until the new threshold matches the one before it (i.e. until convergence has been reached).

This iterative algorithm is a special one-dimensional case of the k-means clustering algorithm, which has been proven to converge at a local minimum—meaning that a different initial threshold may give a different final result.

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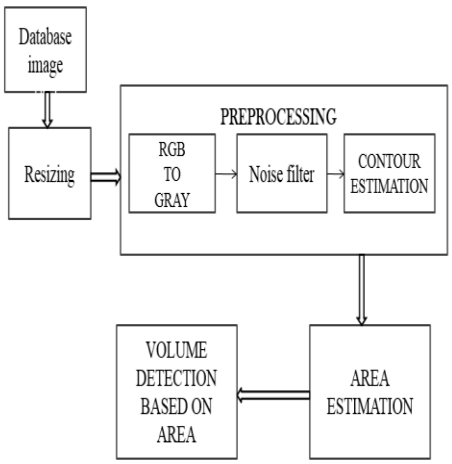
PROPOSED METHOD



Loggabor Lung cancer detection

Steps

1. First enter the patient ID

2. Enter patients mail ID

3. Select Input image cross sectional view of lungs

- After selection the image histogram equalized,
- Gabor filtered enhance the image
- Dilated gradient mask
- Cleared border image
- Calculate area
- Possible location of cancer is traced by green boundary

4. Result

In Existing system, X ray images had been used. Since, X ray imaging techniques are very old and includes the ribs of the chest hence it is very difficult to detect lung cancer in such x-ray images. Hence in the proposed work, it is proposed to consider the CT scan images which only consists of lung portion from the top view of the human body. Still the images consists of several challenges in segmentation.

GABOR FILTERS

In image processing, a Gabor filter, named after Dennis Gabor, is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave.

Simple cells in the visual cortex of mammalian brains can be modeled by Gabor functions. Thus, image analysiswith Gabor filters is thought to be similar to perception in the human visual system.

Its impulse response is defined by a sinusoidal wave (a plane wave for 2D Gabor filters) multiplied by a Gaussian function.[3] Because of the multiplication-convolution property (Convolution theorem), the Fourier transform of a Gabor filter's impulse response is the convolution of the Fourier transform of the harmonic function and the Fourier transform of the Gaussian function. The filter has a real and an imaginary component representing orthogonal directions. The two components may be formed into a complex number or used individually.

Complex

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$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma) = \exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)\exp\left(i\left(2\pi\frac{x'}{\lambda}+\psi\right)\right)$$

Real

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma) = \exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)\cos\left(2\pi\frac{x'}{\lambda}+\right.$$

Imaginary

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma) = \exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)\sin\left(2\pi\frac{x'}{\lambda}+\psi\right.$$

where

$$x' = x\cos\theta + y\sin\theta$$

and

$$y' = -x\sin\theta + y\cos\theta$$

In this equation, λ represents the wavelength of the sinusoidal factor, θ represents the orientation of the normal to the parallel stripes of a Gabor function, ψ is the phase offset, σ is the sigma/standard deviation of the Gaussian envelope and γ is the spatial aspect ratio, and specifies the ellipticity of the support of the Gabor function.

Gabor filters are directly related to Gabor wavelets, since they can be designed for a number of dilations and rotations. However, in general, expansion is not applied for Gabor wavelets, since this requires computation of bi-orthogonal wavelets, which may be very time-consuming. Therefore, usually, a filter bank consisting of Gabor filters with various scales and rotations is created. The filters are convolved with the signal, resulting in a so-called Gabor space. This process is closely related to processes in the primary visual cortex. Jones and Palmer showed that the real part of the complex Gabor function is a good fit to the receptive field weight functions found in simple cells in a cat's striate cortex.

The Gabor space is very useful in image processing applications such as optical character recognition, iris recognitionand fingerprint recognition. Relations between activations for a specific spatial location are very distinctive between objects in an image. Furthermore, important activations can be extracted from the Gabor space in order to create a sparse object representation.

NEURAL NETWORKS CLASSIFICATION

The goal of any supervised learning algorithm is to find a function that best maps a set of inputs to its correct output. An example would be a simple classification task, where the input is an image of an animal, and the correct output would be the name of the animal. Some input and output patterns can be easily learned by single-layer neural networks (i.e. perceptrons). However, these single-layer perceptrons cannot learn some relatively simple patterns, such as those that are not linearly separable. For example, a human may classify an image of an animal by recognizing certain features such as the number of limbs, the texture of the skin (whether it is furry, feathered, scaled, etc.), the size of the animal, and the list goes on. A single-layer neural network however, must learn a function that outputs a label solely using the intensity of the pixels in the image. There is no way for it to learn any abstract features of the input since it is limited to having only one layer. A multi-layered network overcomes this limitation as it can create internal representations and learn different features in each layer. The first

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layer may be responsible for learning the orientations of lines using the inputs from the individual pixels in the image. The second layer may combine the features learned in the first layer and learn to identify simple shapes such as circles. Each higher layer learns more and more abstract features such as those mentioned above that can be used to classify the image. Each layer finds patterns in the layer below it and it is this ability to create internal representations that are independent of outside input that gives multi-layered networks their power. The goal and motivation for developing the backpropagation algorithm was to find a way to train a multi-layered neural network such that it can learn the appropriate internal representations to allow it to learn any arbitrary mapping of input to output.

The backpropagation learning algorithm can be divided into two phases: propagation and weight update.

Phase 1: Propagation

Each propagation involves the following steps:

1. Forward propagation of a training pattern's input through the neural network in order to generate the propagation's output activations.
2. Backward propagation of the propagation's output activations through the neural network using the training pattern target in order to generate the deltas of all output and hidden neurons.

Phase 2: Weight update

For each weight-synapse follow the following steps:

1. Multiply its output delta and input activation to get the gradient of the weight.
2. Subtract a ratio (percentage) of the gradient from the weight.

This ratio (percentage) influences the speed and quality of learning; it is called the learning rate. The greater the ratio, the faster the neuron trains; the lower the ratio, the more accurate the training is. The sign of the gradient of a weight indicates where the error is increasing, this is why the weight must be updated in the opposite direction.

Repeat phase 1 and 2 until the performance of the network is satisfactory.

Algorithm

Algorithm for a 3-layer network (only one hidden layer):

```
initialize network weights (often small random values)
do
   forEach training example ex
      prediction = neural-net-output(network, ex) // forward pass
      actual = teacher-output(ex)
      compute error (prediction - actual) at the output units
      compute Δw_h for all weights from hidden layer to output layer // backward pass
      compute Δw_i for all weights from input layer to hidden layer // backward pass continued
      update network weights // input layer not modified by error estimate
until all examples classified correctly or another stopping criterion satisfied
return the network
```

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As the algorithm's name implies, the errors propagate backwards from the output nodes to the input nodes. Technically speaking, backpropagation calculates the gradient of the error of the network regarding the network's modifiable weights.[2] This gradient is almost always used in a simple stochastic gradient descent algorithm to find weights that minimize the error. Often the term "backpropagation" is used in a more general sense, to refer to the entire procedure encompassing both the calculation of the gradient and its use in stochastic gradient descent. Backpropagation usually allows quick convergence on satisfactory local minima for error in the kind of networks to which it is suited.

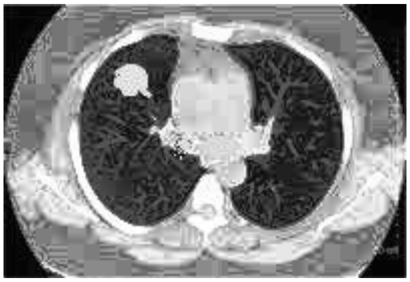
Back propagation networks are necessarily multilayer perceptrons (usually with one input, one hidden, and one output layer). In order for the hidden layer to serve any useful function, multilayer networks must have non-linear activation functions for the multiple layers: a multilayer network using only linear activation functions is equivalent to some single layer, linear network. Non-linear activation functions that are commonly used include the logistic function, the softmax function, and the gaussian function.

The backpropagation algorithm for calculating a gradient has been rediscovered a number of times, and is a special case of a more general technique called automatic differentiation in the reverse accumulation mode.

It is also closely related to the Gauss–Newton algorithm, and is also part of continuing research in neural backpropagation.

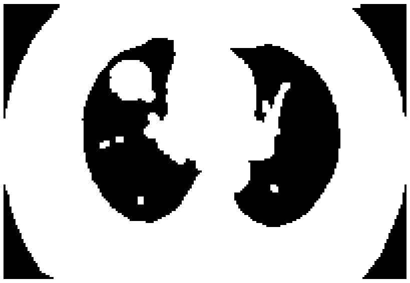
OUTPUTS

original image with histogram equalized



gabor filterd enhanced image

dilated gradient mask



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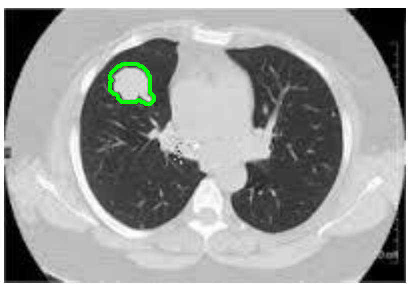
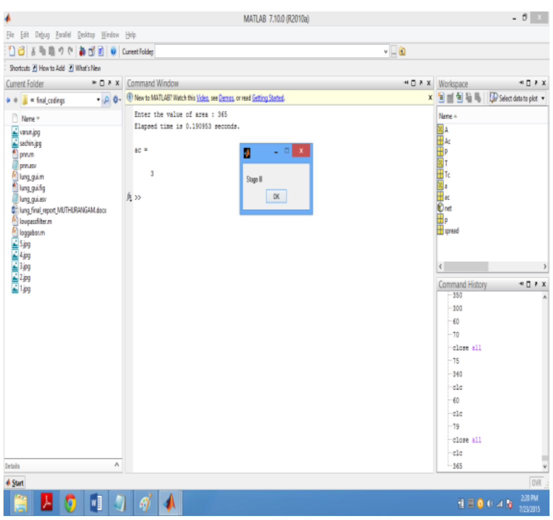
cleared border image

possible location of cancer is traced by green boun

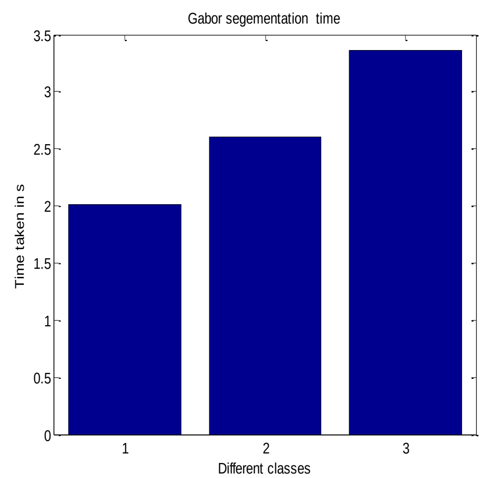




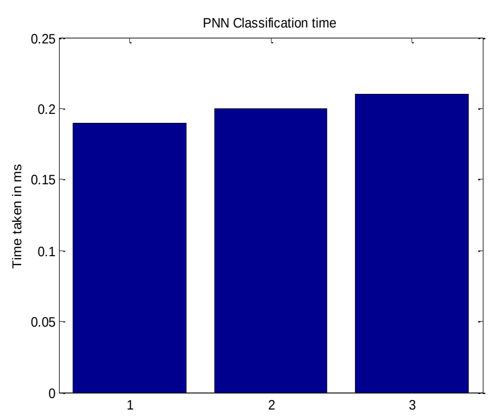
PERFORMANCE ANALYSIS

1. Area accuracy based on noise amount present in the images
2. Time required to detect cancer and classify cancer.

Segmentation time



Classification time



Segmentation time of various methods

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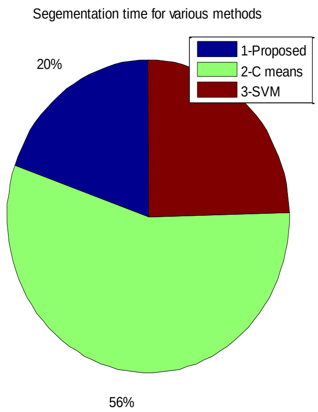

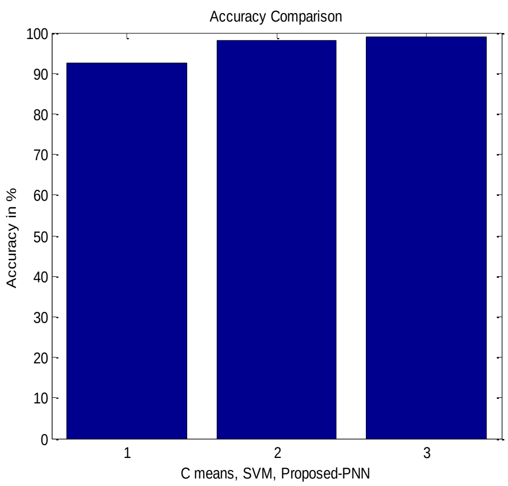

ADVANTAGES

1. Since we use segmentation based method, inspired by human eyes, accuracy is better.
2. This system is an integrated system, which can find even the tissue spoiled on the inner walls of the lungs.
3. The time taken for detection per frame is just 3.36s for stage III cancer. Hence, any prediction of asthma is possible and helpful to diagnosis and future possibility of acquiring asthma.

CONCLUSION

In our proposed work cancer detection and its classification, and the time taken to perform this is continuously monitored. And hence the chronicity of the disease is identified. In addition to this, performance analysis have been performed for segmentation time and classification time. While compared to kmeans, and fuzzy logic based segmentation, the proposed method outperforms the other methods. Over all programming had been done along with a GUI design and several bar graphs and pie charts have been plotted to evaluate the performance of proposed lung cancer detection method. Simulations had been done with matlab software using image processing, and graphical toolboxes.

REFERENCES

[1] WHO, Global Tuberculosis Report. World Health Organization, 2012.
[2 Global Tuberculosis Control 2011. World Health Organization, 2011.
[3] Stop TB Partnership, The Global Plan to Stop TB 2011-2015. World Health Organization, 2011.
[4] S. Candemir, S. Jaeger, K. Palaniappan, S. Antani, and G. Thoma, "Graph-cut based automatic lung boundary detection in chest radiographs," in IEEE Healthcare Technology Conference: Translational Engineering in Health & Medicine, 2012, pp. 31–34.
[5] S. Candemir, K. Palaniappan, and Y. Akgul, "Multi-class regularization parameter learning for graph cut image segmentation,"

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in International Symposium on Biomedical Imaging, 2013, pp. 1473–1476.

[6] S. Jaeger, A. Karargyris, S. Antani, and G. Thoma, "Detecting tuberculosis in radiographs using combined lung masks," in Int. Conf. IEEE Engineering in Medicine and Biology Society (EMBS), 2012, pp. 4978–4981.

[7] C. Leung, "Reexamining the role of radiography in tuberculosis case finding," The Int. J. of Tuberculosis and Lung Disease, vol. 15, no. 10, pp. 1279–1279, 2011.

[8] L. R. Folio, Chest Imaging: An Algorithmic Approach to Learning. Springer, 2012.

[9] S. Jaeger, S. Antani, and G. Thoma, "Tuberculosis screening of chest radiographs, spie.org/x48510.xml (last accessed September 2013)," SPIE Newsroom, 2011.

[10] C. Daley, M. Gotway, and R. Jasmer, "Radiographic manifestations of tuberculosis," A primer for Clinicians. San Francisco: Francis J. Curry National Tuberculosis Center, 2009.