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Lung Region Segmentation using Image Data Analysis

[1]Ms.S.Pradeeba, [2]Dr.S.Kumar Ganesh

[1]M.E. Scholar, Dept of Communication Systems, Paavai Engineering College, Namakkal, Tamilnadu, India
[2]Associate Professor, Dept of ECE, Paavai Engineering College, Namakkal, Tamilnadu, India

***Abstract* - It is very common in medical imaging that the anatomy of interest occupies only a very small part of the image. Therefore, most of the removed spots are in the background area, while these small organs (anomalies) are of greater importance. One of the most difficult tasks in analyzing medical images is the segmentation of medical images, which identifies pixels or organ damage from medical background images such as CT or MRI images. The main goal of the lung region extraction process is to capture the lung region and determine the regions of interest (ROI) on the CT image.**

Keywords: Medical image segmentation, Lung segmentation, Deliver critical information, CT image analysis.

I. INTRODUCTION

One of the most difficult tasks in analysis is the segmentation of medical images that identify pixels or organ damage from medical background images such as CT or MRI images. Medical images that include the provision of critical information on the shapes and volumes of these organs. Many researchers have proposed various automated segmentation systems using available technologies. Earlier systems were based on traditional methods such as edge detection filters and mathematical methods. Second, machine learning approaches that extract handmade features have become a dominant technique over a long period of time. The design and extraction of these features has always been the primary concern when developing such a system, and the complexity of these approaches has been seen as an important obstacle to its implementation. In the 2000s, deep learning approaches emerged due to the improvement of the material and demonstrated their considerable skills in image processing tasks. The promising ability of deep learning approaches has made it a preferred option for image segmentation and especially for medical image segmentation. Particularly in recent years, image segmentation based on deep learning techniques has received a lot of attention and underlines the need for a complete revision. To the best of our knowledge, there is no comprehensive review specifically conducted for the segmentation of medical images using deep learning techniques. There are current research articles on the segmentation of medical imaging. When examining different types of medical imaging analysis, however, little attention was paid to the technical aspects of segmentation of medical imaging. Many other sections of medical image analysis are also covered, e.g. Classification, detection and recording.

Therefore, medical image analysis analysis is not a specific medical image segmentation investigation. Due to the large area covered in this article, details, functions and gaps in the network are missing. This article consists of three main sections, approaches (network structures), training techniques and challenges. In the Network structure section, the most important common network structures that are used for image segmentation are presented.

Figure 1: Flow chart for system model

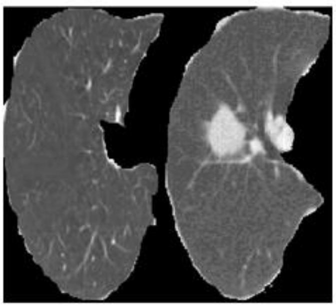

Figure 2: Normal Lung vs Lungs with Tumor

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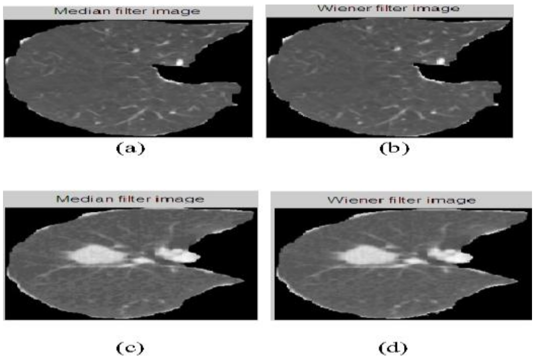

Figure 3: Segmentation Process

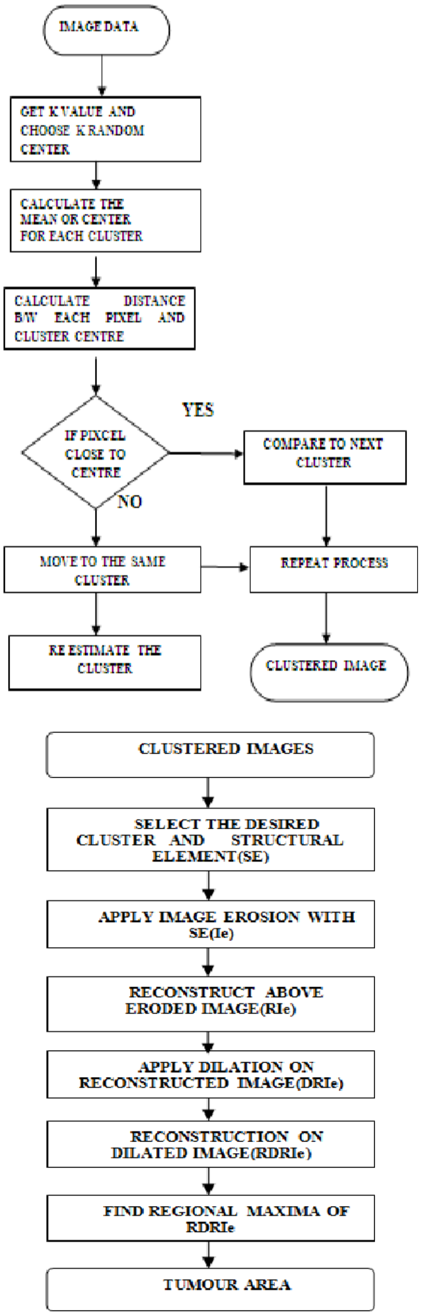

Figure 4: Segmentation Process Flow Chart

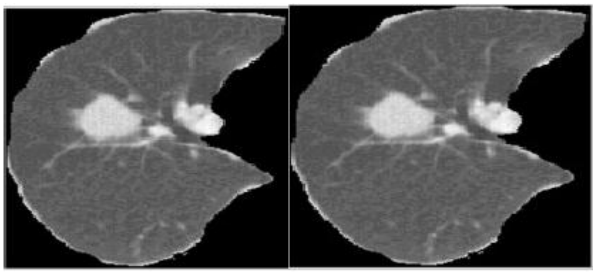

Figure 5: Extracted Tumor Area of Lung

It was developed to cover the resulting sequence of structures. Here we try to approach the most important structures with greater superiority than the ancestors. The Training Techniques section explains the advanced techniques used to create models for deep neural networks. The Challenges section addresses various types of challenges related to segmenting medical images using deep learning techniques. These challenges relate primarily to network design, data, and training. This section also offers possible solutions based on the literature to address the individual challenges associated with network design, data and training.

II. LITERATURE SURVEY

A new CAD (Computer Aided Detection) system by A. R. Talebpour et al. (2014), which detects small nodes (3 mm larger) on high resolution CT (HRCT) images. In the first step, the lung region is removed, and then suspected cases are justified with a 3D filter node type. In the last step, a neural network is used to reduce false alarms. A cylindrical filter is used to filter instances of nodes from other objects in images. Detection performance was evaluated experimentally using the LIDC pulmonary imaging database. Reasonable results show that the nodes on the images can accurately capture HRCT using the 3D model and reduce the FP based on object analysis.

In recent years, image processing techniques have been widely used in various medical fields to improve the levels of pre-detection and processing, for which time or duration is very important in identifying the disease in the patient. as close as possible. can be rapid, especially for many tumors such as lung cancer, breast cancer. This system first segregates the area of interest (lung) and then analyzes the acquired area separately to detect nodes to examine the disease. Even with the different lung tumor segmentations presented, methods to improve tumor segmentation are still of interest because CT images of the lung tumor have certain complex properties, such as wide variation in appearance and appearance. To solve this problem, the grouping procedure performed a tumor segmentation procedure by CT imaging that separates uninfected lung tumors from healthy tissue. The proposed

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method uses a preprocessing technique that removes unwanted are facts through Central and Vienna filters. First, the segmentation of the CT images was performed using the K-means clustering method. Average EK grouping is used for the grouped result. In addition, features such as entropy, contrast, correlation, homogeneity and surface are extracted from the tumor section of the fuzzy segmented Ek-Media image. A statistical method called Gray Level Co Incident Matrix (GLCM) is used to extract the features. The classification is done through the monitoring neural network, referred to as the Back propagation Network (BPN). The classification results indicate whether the CT image is normal or cancerous.

Cancer detection is usually done manually by qualified professionals. These techniques are of great assistance in the detection of high detection. They are also involved in a very long process and are highly dependent on the individual. This gives the high probability of human error occurring in the detection process, which requires an automated process. Thus S. Kalaivani et al. (2017) on early detection of cancer through an automated process to minimize human error and make the process more precise and easier. In the proposed work, image processing algorithms and artificial neural networks were used to design an automated process for early detection of lung cancer.

Early detection of lung cancer is very difficult with pathological tests. Over the past few decades, many CAD systems for early detection of lung tumors have been developed to support radiologists. Jaspinder Kaur et al. (2014) present a CAD system that uses computed tomography images to identify tumors at an early stage. The lung regions on the CT images are partitioned using the optimal threshold. Identifying the region of interest the regional growth method is used. Two types of structural and statistical parameters are calculated and analyzed separately. The set of functions is applied to the multilateral feed feedback propagation network. The performance of the backward propagating neural network is measured as the mean square error (MSE). The classification accuracy of the system is 98% and the mean of a minimum square error. The system is implemented in MATLAB and the processing time for the classification is 0.22 seconds.

Lung cancer is the most common cancer among many cancers with the highest mortality rate. The fact that the nodes that form in the lungs have different shapes, such as B. round or spiral, is difficult to see in some cases. Early diagnosis facilitates identification of stages of identification and increases the success rate of treatment. In this study, a holistic computer-assisted diagnosis (CAD) system using computed tomography (CT) imaging to enable early diagnosis of lung cancer and the distinction between benign and malignant tumors was developed by Emre Dandil et al (2014). The designed CAD system enables the segmentation of nodes in the lobes with the SOM neural network model (Self-Organized Maps) and ensures the classification between benign and malignant nodes using the ANN (Artificial Neural Network).

Convolutional neural networks (CNN) have achieved top performances for automatic segmentation of medical images. However, they did not show results that were accurate and robust enough for clinical use. In addition, they are limited by the lack of specific image adaptation and the generalization of unprecedented classes of objects (also known as zero learning). To solve these problems, Guotai Wang et al. (2018) presented a new interactive segmentation framework based on deep learning by integrating CNN into a bounding box and a scribbling-based segmentation pipeline. Accurate adjustment of the image is recommended to adapt the CNN model to a specific test image that can be monitored (without additional user interaction) or monitored (with additional doodles). It also provides a loss-weighted function that takes into account uncertainty and network-based interaction for refinement.

Bottom-up training in a controversial deep neural network (CNN) is difficult because it requires a large amount of labeled training data and extensive experience to ensure proper convergence. Another promising alternative is to modify previously formed CNNs using, for example, a large number of labeled natural images. However, significant differences between natural and medical images can hinder such knowledge transfer. Nima Tajbakhsh et al. (2016) attempt to answer the following central question for medical image analysis: Can the use of deep preformed CNNs with adequate adaptation eliminate the need to train CNN? Earth from the beginning? To answer this question, four different medical imaging applications were examined in three specialist areas (radiology, cardiology and gastroenterology), in which the depth of CNN performance training was classified, created and segmented from the beginning.

Segmentation and classification of multi-view magnetic resonance (RM) imaging. This hybrid by Wilburn E. Reddick et al. (1997) present a fully automated process for the neural network method, in which a self-organized Kohonen neural network is used for segmentation and a multilateral neural network with reverse expansion for classification. To separate different tissue types, this procedure uses T1, T2 and PD-weighted MRI images derived from clinical examinations. Volume measurements of brain structures in intracranial volume for a cross section of the index were calculated in 14

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normal subjects (average age 25 years; seven males, seven females). This index cut was at the level of the central gray nucleus, encompassing the genus and splenius of the corpus callosum, and generally indicated placement of the name and lateral ventricle. Intra class correlation of this automated segmentation and tissue classification with the acceptable radiological identification standard for the index cutoff in the 14 volunteers showed coefficients (ri) of 0.91, 0.95 and 0.98 for the white substance, gray substance and ventricular cerebrospinal Liquid.

III. EXISTING METHODOLOGY

It is very common in medical imaging that the anatomy of interest is only a very small part of the image. Thus, most of the spots are removed in the background area, although these small organs (anomalies) are of greater importance. One of the most difficult tasks in image analysis is medical image segmentation, which identifies pixels or organ damage from medical background images as CT or MRI images. The primary goal of the lung region extraction process is to capture the lung region and determine the regions of interest (ROI) on the CT image. Figure 3.1 shows the block diagram of the lung segmentation system.

In general, a chest CT picture includes not only the region of the lung, but also the chest, heart, liver and other areas of the organ. The primary goal of the lung region extraction process is to capture the lung region and determine the regions of interest (ROI) on the CT image. The seven steps of the computerized diagnostic system for removal of the lung region are as follows:

- Bit Plane Slicing
- Erosion
- Median Filtering
- Dilation
- Outlining
- Lung Border Extraction
- Flood Fill Algorithm

3.1 Bit Plane Slicing

Bit plane slicing is used to highlight the contribution made to the total image appearance by specific bits hence it is useful for analyzing importance played by each bit of the image. In bit plane slicing each pixel is represented by 8 bits, the image is composed of eight 1-bit planes. Plane one is composed of least insignificant bits and if all these 1-bit planes are combined we will get the most insignificant image (to the right side of the original image in above example).Plane 8 contains the most significant bits and when all the plane 8 bits are combined we will get the most significant and clear image (the one to the lower right of the above example), thus in bit plane slicing only the higher order bits contain the visually significant data

3.2 Erosion

Morphology operations can be characterized as a gathering of image processing procedures that process images taking into account shapes. These morphological operations are taking into account applying an organizing component to an input image keeping in mind the end goal to make a yield image of the same size. In such operation, the estimation of every pixel in the yield image is taking into account an examination of the comparing pixel in the information picture with its neighbours. This is carried out by picking the size and state of the area. At that point, we can build up a morphological operation that is delicate to particular shapes in the input image. The structure element is a matrix consists of 0's and 1's, where the 1's are called the neighbours. The value of each pixel in the output image is set according to a comparison of the corresponding pixel in the input image with its neighbours. It has many shapes according to its application. The most common and basic morphological operations are dilation and erosion. Dilation is to add pixels to the boundaries of objects in an image, while erosion is to remove pixels on object boundaries. The number of pixels that are added or even removed from the structure in an image depends on the size and shape of the structuring element that is used to process that image. In these morphological operations, the condition of any given pixel in the output image can be determined by applying a rule to the studied pixel and its neighbours.

3.3 Median Filtering

Anti-bias is an image processing technique used to reduce noise in an image and create a less clear image with fewer pixels. Most smoothing techniques are based on low-pass linear filters. It is based primarily on the technique of the media of the input image or the technique of the median. To make a smoothing process, we apply a filter to our image. The most common types of filters are linear filters, i.e. B. the median filter. The median filter is used to track the image. The filtering medium is a non-linear method for removing noise. It is widely used because it is very effective in removing noise and preserving edges. The median pixel-to-pixel filter moves through the image and each value is replaced with the mean of neighboring pixels. The proximity pattern that moves pixel to pixel throughout the entire image is called a "window". The median is calculated by first arranging all the pixel values in the window in numerical order and then replacing the estimated pixels with the average (median value) of the pixels. It prevents fluctuations or other small picture fluctuations. is

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equivalent to a high frequency rejection in the frequency domain. Makeup also has sharp edges that contain important image information. B = medfilt2 (A [m, n]) averages the filtering of matrix an in two dimensions. In each output pixel the average value is close to m x n around the corresponding pixels in the image.

(a) (b)

Figure 6: (a) Eroded image (b) Median filtered image

IV. RESULT AND DISCUSSION

The experiments were performed in MATLAB platform. CT images are taken from internet. The main objective of this work is accurate lung segmentation from a CT image. Fig 7 shows the original lung CT image which is processed in MATLAB to segment the lung region from the background.

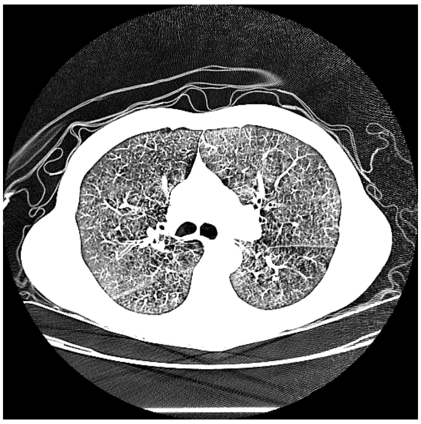
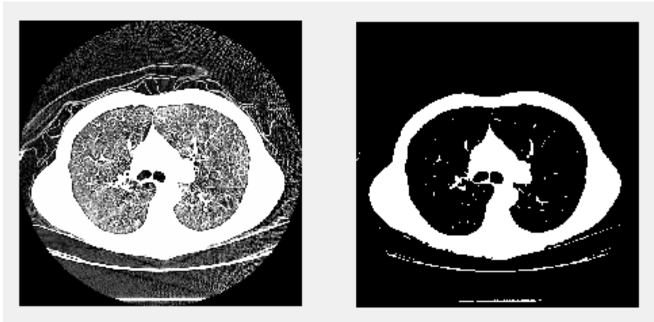


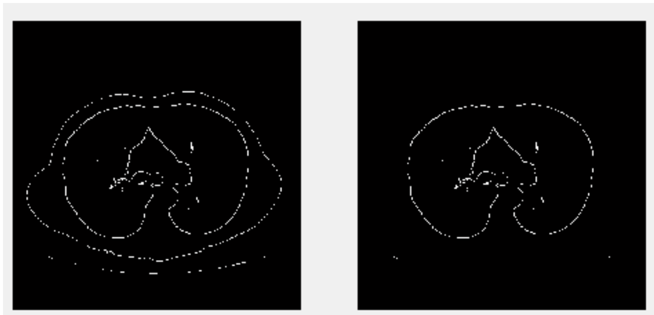
Figure 7: The original lung CT image

Fig 8 shows the step by step result of lung segmentation process. Fig 8 (a) shows the bit plane slicing image. After bit plane slicing morphological erosion is applied, which is shown in fig 8 (b).the eroded image is given to median filter to remove noise is in fig 8 (c). Then the filtered image is processed by dilation that is shown in fig 8 (d).next outlining is applied to lung region shown in fig 8 (e). Lung border extraction is shown in fig 8 (f) then these border is filled using blood fill algorithm shown in fig 8 (g). Finally, the segmented lung region is shown in fig 8 (h).

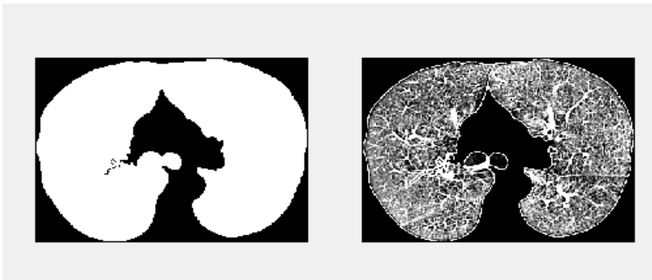


(a) Bit plane slicing **(b) Erosion**

(c) Median filter **(d) Dilation**



(e) Outlining **(f) Lung border extraction**



(g) Flood fill algorithm **(h) Extracted lung**

Figure 8: Results for each step in lung region segmentation

V. CONCLUSION

In this document, we first summarize the most popular network structures for the segmentation of medical imaging and highlight their advantages over ancestors. Next we present an overview of the most important training techniques for

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segmentation in medical imaging, their advantages and disadvantages. In the end, we focus on the key challenges associated with the deep learning solution for segmenting medical imaging. We discussed effective solutions for various challenges. We believe that this article can help research choose the right network structure for your problem while paying attention to potential challenges and solutions. All signs show that deep learning approaches will play an important role in segmenting the medical image.

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