LEHIGH UNIVERSITY
DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CSE 498: Computer Vision

Project Report

Lung Segmentation

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Contents

1 Member list & Workload

No.	Full name	Percentage of work
1	Abhishek Srivastava	50%
2	Kaushik Jagani	50%

1.1 Abhishek Srivastava

1. Data Acquisition: [2022-10-23, Sunday] The data acquisition task is complete, and we will be using China data set to perform segmentation of Chest X-ray images.

2. Labeling [2022-10-23, Sunday] The data set chosen already has the mask of left and right lung available and will be used as ground truth for segmentation. For this reason, the Labelling was not performed in this exercise. Primarily China dataset was selected because the team has limited expertise to correctly label mask (ground truth) on original X-Ray images without any assistance from medical expert.

3. Model development:
   (a) A set of traditional methods – Region based; Clustering based methods
   (b) Learning based methods

4. Model Evaluation and parameter tuning of respective models

5. Report and summarize the model results

1.2 Kaushik Jagini

1. Data Parsing and Data cleaning: [2022-10-23, Sunday] A script was written to successfully import the data from our local drive to a python notebook. Initial pre-processing related to traditional segmentation methods.

2. Model development:
   (a) Remaining set of traditional methods – Watershed method; Edge based method
   (b)Learning based methods

3. Model Evaluation and parameter tuning of respective models

4. Report and summarize the model results

Both candidates would attempt to research across the task assigned to deliver insights into each other's work. Model development and evaluation are the tasks where a higher level of collaboration is required and intended.

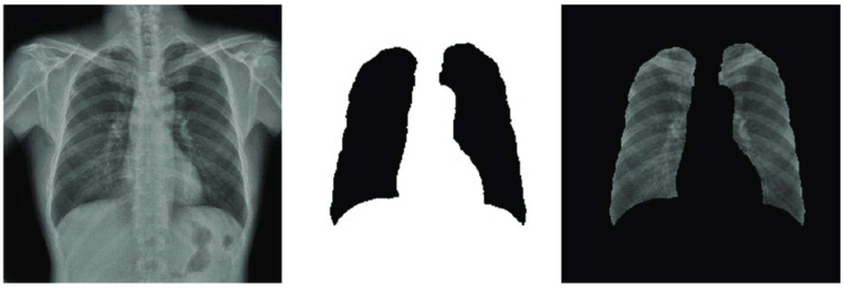

Figure 1: Lung Segmentation

2 Problem Statement

Surgery planning, disease diagnosis, and prognosis all depend on being able to accurately identify organ boundaries in medical pictures. The technique of correctly separating the regions and borders of the lung field from surrounding thoracic tissue is known as lung segmentation, and it is a crucial first step in pulmonary image processing for many clinical decision support systems. In this study, we suggest an approach based on deep learning for segmenting the lung regions in chest X-rays and eventually classify diagnosis of patients using the segmented image as an input to the classifier model. Figure 1 shows basic lung segmentation outputs.

3 Motivation

Additional computer analysis of these anatomical regions is available when lung fields are accurately defined. This enables the extraction of clinically relevant features that can be used to train a machine learning algorithm for the detection of disease and anomalies. In order to improve the caliber of care and patient outcomes, these computational tools can assist physicians in making rapid, precise diagnoses. For chest disorders such lung cancer, pulmonary edema (fluid in the lung), pleural effusion (fluid between the lung and chest cavity), pneumonia (infection by bacteria, viruses, fungus, or parasites), and tuberculosis, chest radiography is the most often used diagnostic imaging test (bacterial infection). Chest disorders cause more than 10 million deaths worldwide each year. According to a survey, 6.3 million people died from ischemic heart disease [3], 4.3 million from lower respiratory infections, 2.2 million from chronic obstructive pulmonary disease, 2 million from tuberculosis [6], and 0.9 million from other chest disorders in 1990 (lung cancer) [2]. Many treatments are only effective in the early, symptomless stages of most diseases. For accurate lung CT image analysis, such as lung cancer detection, lung image segmentation is a necessary step. The change in the visual extent of the disease over time is an essential measure of response to therapy and a predictor of death, and it can be used to quantify the progression, regression, or stagnation of lung disease. Additionally, segmented lungs can be employed for image registration, particularly in 3-D scans. As a result, the radiologists will be able to assess the volumetric changes in the lungs and determine the percentage of the patients' healthy parenchyma region that has been functionally reduced.

4 Literature Review

The delineation of anatomical features and other regions of interest is automated or made easier with the help of medical picture segmentation, which is essential in many imaging applications. Since the last ten years, the segmentation of lung fields in chest X-rays (CXR) have gained a lot of attention in the literature. For this work, a thorough review of lung segmentation methods for chest radiographs was conducted.

Much of the works mentioned used the JSRT dataset [1] as their image database. The Japanese Society of Radiological Technology (JSRT) created a database of chest radiographs (with and without lung nodules) and made it available to the public along with its ground truth clinical data. Only two studies, as far as we are aware, have used portable radiography of the chest. This demonstrates the lack of research on portable chest radiographs, which are extremely crucial, especially for critically ill patients.
Early segmentation techniques for CXR were divided into four groups: rule-based techniques, pixel classification-based techniques, deformable model-based techniques, and hybrid techniques [5]. A rule-based scheme includes a series of actions, tests, and rules. The techniques include local thresholding, region growth, edge and ridge detection, morphological procedures, fitting of geometrical models, functions, and dynamic programming. Pixel classification-based technique, on the other hand, is more generic and basically models the intensities of the picture and classifies the pixels into lung field or background. The rule-based scheme is presented using Bezier interpolation of prominent control points. used the fuzzy clustering method (FCM)-based scheme, and one of their comparison outcomes was the post-processed pixel classification approach.
Although it has numerous limitations when used to apply towards discovering appropriate groups in data analysis tasks, the FCM method[9] is the most well-known. To have a more reliable FCM, several researchers have attempted to change the fundamental goal function. FCM has been utilized with some success in the soft or fuzzy segmentation in medical imaging of chest CT, chest MRI, and brain MRI, even though the perfect segmentation of an image is often application dependent. The authors' motivation to use the FCM in their study came from the ease with which the borders of the lung or brain could be seen in CT and MRI images thanks to the unique bone and cell tissue. In their study, Rastgarpour et al.[14] merged a local region-based level set approach with a version of fuzzy clustering in order to segment a few modalities and body parts, including the lung, Gong et al. [13] applied FCM with spatial constraints to segment the lung for CXR. The literature also contains a few publications on additional FCM-based CXR applications. In their implementation of the algorithm for pneumonia identification, Parveen et al. also employed feature vectors to cluster feature data for atypicality detection by segmenting cardiac information (size, contour, and shape). The inhomogeneities of X-Ray imaging are mostly to blame for the paucity of work on lung segmentation for CXR utilizing FCM. FCM is difficult to utilize as a segmentation technique because of the sharp edges at the clavicle and rib cage regions as well as the intensity fluctuation around the lung area.
The deformable model-based approaches represent a recently developed system that has been thoroughly investigated and applied in medical picture segmentation. Lung area segmentation has been effectively used to this shape-flexibility model, Active Shape Model (ASM) and Active Appearance Model (AAM) [11]. But both have several drawbacks and restrictions, such as the need for manual initialization and supervision when changing parameters, which results in very variable solutions. The creation of the hybrid scheme aims to improve segmentation outcomes by combining the strategies mentioned previously. Many hybrid algorithms discovered in the literature mix rule- and shape-based techniques, which is quite intriguing to observe. However, the ASM-fused approaches have limitations, whereas the form schemes need computing complexity, learning, and training as well as the optimization process.

5 Scope of the Project and Tangible Goals

All of us are aware COVID-19 recently affected everyone worldwide with 95,700,347 incident cases with 5,327,014 hospitalization in united states alone. Tuberculosis and pneumonia are also two highly prevalent disease around the world and lung segmentation could help physicians in early and accurate diagnosis of such diseases and hence could save many lives or reduce the overall healthcare resources by significant margin.
By accurately segmenting lungs and identifying boundaries with 100% precision, we could feed this data into

classification models which can classify patients of distinct types of pneumonia with significantly higher accuracy. Although, the scope of this exercise is limited to deriving an approach to automate segmentation of lung given chest X-rays, but this could well be extended as an input to other classification model in downstream. Depending on the availability of time, we would also attempt to classify Tuberculosis patients (normal vs sick) in our selected dataset.

6 Project Plan and Deadlines

The following steps are essential parts of the complete segmentation and classification performed on the selected chest X-Ray data.

6.1 Data Acquisition

We planned to use chest X-ray data (Montgomery County X-ray Set), which is publicly available. The dataset contains x-rays and corresponding masks. Some masks are missing so it is advised to cross-reference the images and masks. X-ray images in this data set have been acquired from the tuberculosis control program of the Department of Health and Human Services of Montgomery County, MD, USA. This set contains 138 posterior-anterior x-rays, of which 80 x-rays are normal and 58 x-rays are abnormal with manifestations of tuberculosis.
After exploring more datasets Shenzhen Hospital X-ray Set / China data set [4], CheXpert dataset and, JSRT dataset / Japanese dataset we finalized China data set as an input for the segmentation algorithm. Our decision was based on factors – Sample size of the dataset, availability of mask which can be used as ground truth for evaluate segmentation method and, availability of ground truth labels for disease classification

6.2 Data Parsing and Cleaning

Because the data of interest contains images in PNG format, they need to be appropriately handled while importing them to python and conversion to numpy arrays.

6.3 Labelling

There are many existing tools to create labelled masks for images, including Labelme, ImageJ, and even the graphics editor GIMP. While these are all great tools, they cannot be integrated within a Jupyter notebook, making them harder to use with many existing workflows. Fortunately, Jupyter Widgets make it easy for us to make interactive components and connect them with the rest of our Python code. However, in this exercise we did not need to perform manual labelling because the data set already has mask labels.

6.4 Develop Model on training data

6.4.1 Traditional Methods

Some of the traditional methods of image segmentation are shown in Figure 2.

6.4.2 Deep Learning Based Methods

U-NET architecture (See Figure 3) was originally developed for medical image understanding and segmentation. It has vast applications in the domain and has been a key architecture in the medical imaging automation society. The architecture of this network includes two main parts: contractive and expansive. The contracting

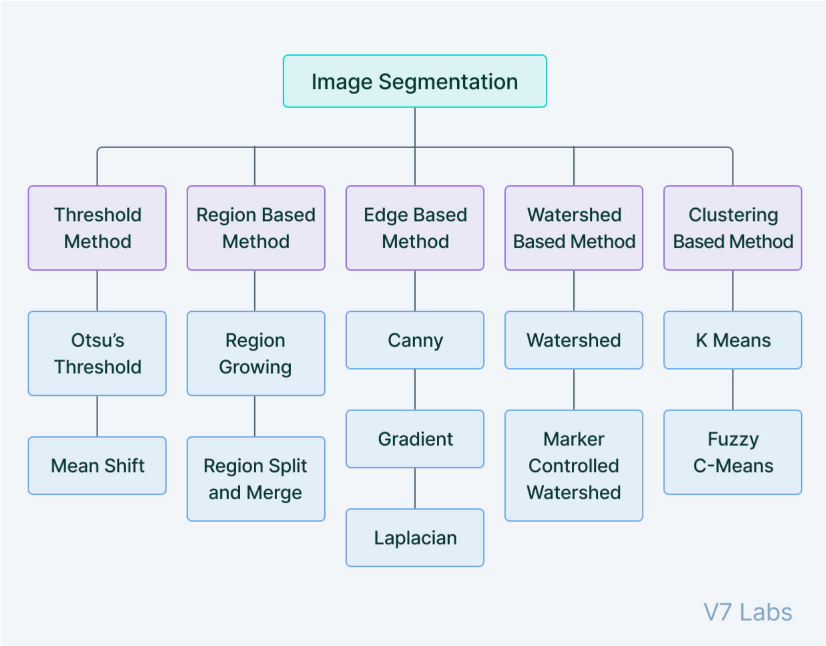

Figure 2: Traditional methods for image segmentation [8]

path consists of several patches of convolutions with filters of size 3×3 and unity strides in both directions, followed by ReLU layers. This path extracts the key features of the input and results in a feature vector of a specific length. The second path pulls information from the contractive path via copying and cropping, and from the feature vector via up-convolutions, and generates, by a successive operation, an output segmentation map. The key component of this architecture is the operation linking the first and second paths together. This linkage allows the network to attain highly accurate information from the contractive path, thus generating the segmentation mask as close as possible to the intended output.
After exploring other deep learning methods like RNN and LSTM, we developed an understanding that since our dataset would contain 2-D X-Ray images, and we would not have any sequential information in any manner, CNN (U-Net) is better choice for our use case of segmentation. Hence, we would not be implementing RNN for image segmentation.
Similarly, Along with UNET, we researched about other available deep learning models like VNET, SEGNET and UNET++. However, we realised that VNET is more suitable to volumetric segmentation tasks. But in our case it is not a 3d volume to start off with. Out of Segnet and UNET ++, segnet is primarily motivated by road scene understanding applications which require the ability to model appearance (road, building), shape (cars,pedestrians) and understand the spatial-relationship (context) between different classes. UNET++ on the other hand is more suitable to our objective. In simple words, it is an even better version of UNET that can promise to overcome the limitations of UNET which requires extensive architecture search or inefficient ensemble of models of varying depths.
*We intend to explore more potential methods for image segmentation which could work better, specifically for medical images.

6.4.3 Parameter hyper tuning on Validation data

Primarily we would apply randomized grid search to optimize parameters using validation dataset. Both Grid Search and Randomized Grid Search are what we could call a "brute force approach," meaning that the

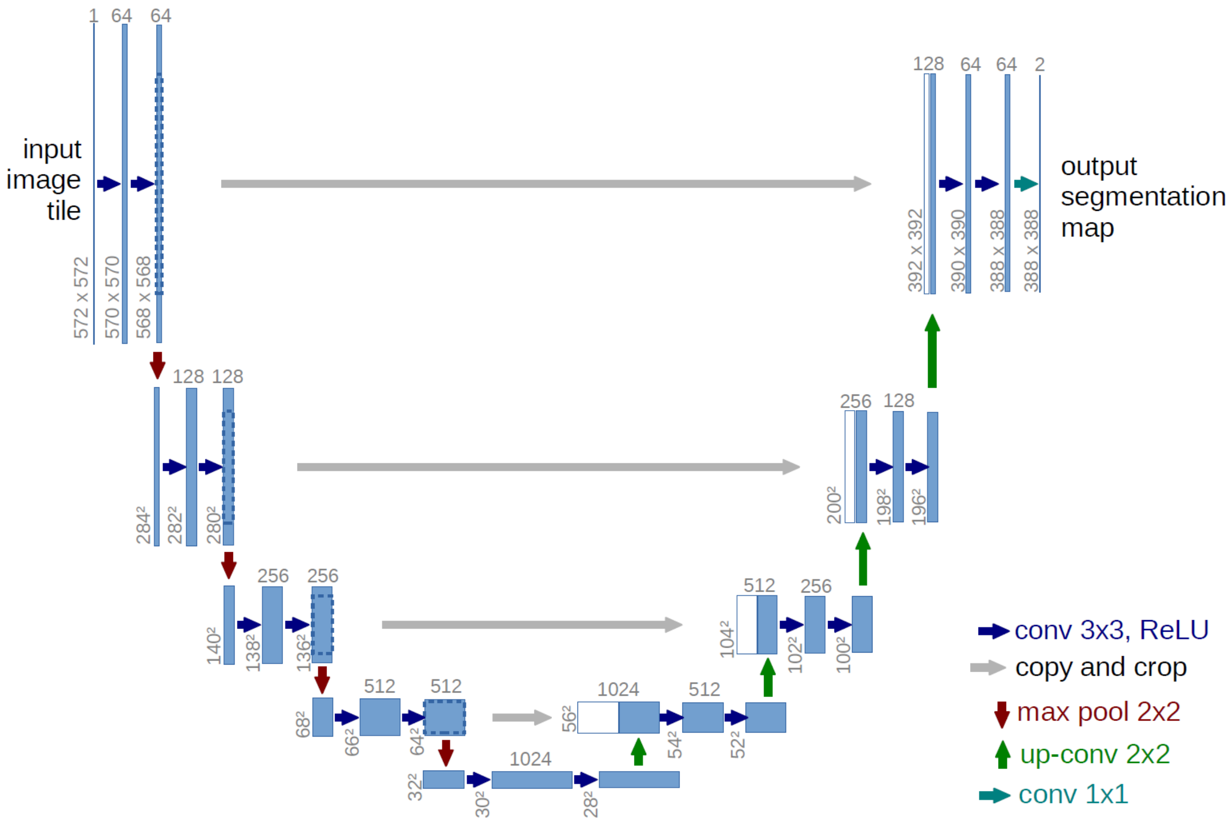

Figure 3: U-Net Architecture [7]

choices of hyperparameters are not in an informative way.

However, there are more informed methods to perform optimization of parameters – Bayesian and Genetic Algorithms. In this exercise, we would limit our work to randomized grid search as shown in Figure 4

6.4.4 Segmentation Model evaluation on test data

The performance of the proposed segmentation algorithm is measured using a 'goodness' index. For two class segmentation problems such as lung and background in this work, one can distinguish true positive (TP) area (correctly classified as lung), false positive (FP) area (background incorrectly classified as lung), false negative (FN) area (lung incorrectly classified as background) and true negative (TN) area (correctly classified as background). Measures such as sensitivity, specificity, accuracy and overlap score can be computed using these values. In this work, the analyses will be performed to both right and left lungs using the following formulas:

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \tag{1}$$

$$IOU = (TP)/(TP + FP + FN) \tag{2}$$

$$Sensitivity/Recall(R) = TP/(TP + FN) \tag{3}$$

$$Specificity = TN/(TN + FP) \tag{4}$$

$$Precision(P) = TP/(TP + FP) \tag{5}$$

$$Fscore(F) = 2PRP + R \tag{6}$$

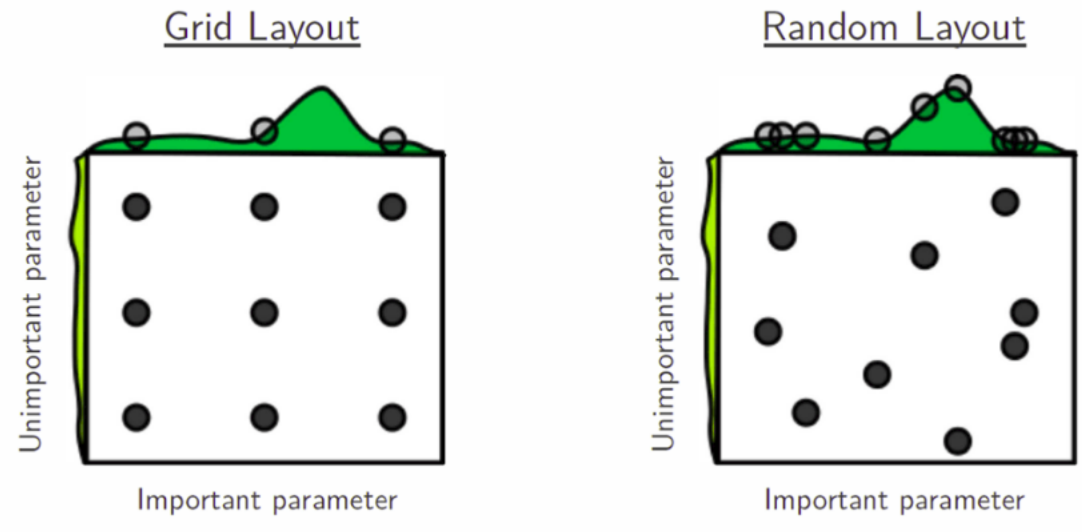

Figure 4: Grid Layout [10]

where, IOU=Intersection over union, and TP, TN, FP, FN are True Positive, True Negative, False Positive, False Negative, respectively.
In addition to the above evaluation metrics, "Execution time" would also be used as another metric to comment on computational efficiency of the segmentation method. The mentioned metrics are also applicable to classification model for disease classification.

6.4.5 Highlight limitations and capabilities of the model

We will attempt to highlight the limitations after evaluating the keys metrices like IOU, Dice score, precision and execution time. These limitations could be related to the assumptions we may make to train our model.

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