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# 80245013 Advanced Machine Learning Project Proposal

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ALBERT MILLAN – 2019280366  
BASTIEN BEDU – 2019280421  
HENRY XIANG – 2019280023

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# 1 Problem Statement

The aim of this project is to train an AI algorithm to accurately predict the existence of pneumothorax (collapsed lung) within images and indicate the location and extent of the condition using masks.

## 2 Motivation

Pneumothorax is often a serious health condition, and can even be life threatening in certain cases. By creating AI systems that can accurately help to diagnose both the presence, extent and location of pneumothorax within patients, we can help doctors in a variety of clinical situations. For example, AI can be used to triage chest x-rays for priority interpretation [1], as well as work alongside doctors to aid them in confirming their own diagnoses and interpretations of x-rays. We hope this AI can make diagnoses more accurate and efficient, as AI in medical imaging continues to advance and save lives.

## 3 Techniques

Considering the task is an image classification problem, we will initially compare the outcome of two distinct methods, namely *support vector machines* (SVM) and *convolutional neural networks* (CNN). These methods have been proven to be successful in the identification of patterns or objects within images, and have been thoroughly studied in the literature [2, 3], including hybrid implementations of the two methods in similar fields of study [4]. We will then identify the best performing method and optimize it, evaluating the existing variants of the proposed method<sup>1</sup>.

An efficient solution of the aforementioned problem must be able to complete the following tasks [8]:

- **Denoising.** Remove noise from the original image.
- **Segmentation.** Segment the image, highlighting the tumor region.

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<sup>1</sup>For instance, multiple CNN models can be implemented to solve a given problem, but only one can yield the best result based on the problem. Examples include ResNet [5], Densely Connected CNN [6] or ResNeXt [7]

- **Classification.** Classifying the tumor as bening or malign.

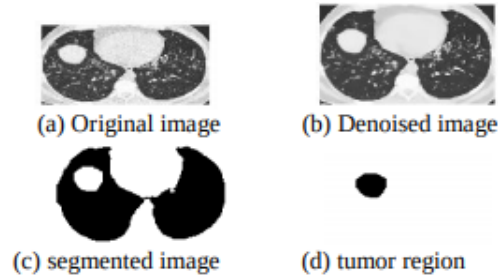


Figure 1: Expected procedure to classify images.

## 4 Data

### 4.1 Input Data

The provided dataset contains a) the set of images in DICOM format<sup>2</sup> b) an array of pixels specifying the segmentation of the image. That is, a 1D array representation of the areas of the image where the lung is collapsed. This array is known as the Run Length Encoding (RLE) mask. If the lung is healthy, the value assigned to the mask is -1.

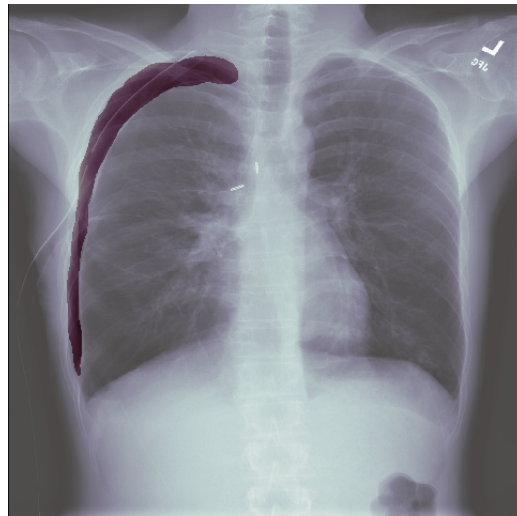


Figure 2: Collapsed lung mask on a X-ray image.

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<sup>2</sup>Method to encode all of a single patient's data within a file. Includes an image, but also other information such as age, gender, etc.

The darker area corresponds to the mask of the collapsed lung. For the test data, the annotation corresponding to the collapsed lung are not provided.

## **4.2 Output Data Format**

We generate a csv file, and for every image in the test dataset we append an entry stating the image id and the aforementioned mask.

## **4.3 Datasets**

The set of ten thousand images and the corresponding dataset can be obtained from the American College of Radiology (ACR), Society of Thoracic Radiology (STR), MD.ai and SIIM. This dataset can be downloaded on the Cloud Healthcare API. The dataset authors provide a python script to download the training and testing data from google cloud. Notwithstanding, we are considering downloading all the data together and split it randomly at an 80-20% ratio for training and testing accordingly. This is still subject to further discussion. Further information can be found in [9].

## References

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