Capstone Project 2 final report: Data Science Bowl 2017

Zexi Yu

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Abstract

In this report, A convolutional neural network is used to solve the tumor recognition problem in CT images proposed by data science bowl 2017 competition. The given CT image is first transformed into the Hounsfield Unit, and several morphology operations is used to segment nodes structure within the lung area. Finally, a CNN is used to recognize tumor patterns. The result does not excel for a variety of reasons, and further works will be done to improve the performance.

1 Introduction

This is my final report for my second capstone project of DataScience Career Track. The goal of this project is to challenge me and to learn more advanced methods in machine learning area. With this reason, the problem of this project is selected as the data science bowl 2017 from kaggle website. Here is a link to the competition page: https://www.kaggle.com/c/data-science-bowl-2017. During this project, I find it useful to learn from several open notebooks for this competition, you can find them in the discussion panel: https://www.kaggle.com/c/data-science-bowl-2017/discussion.

In summary, the goal of the competition is identifying lung cancer given high-resolution CT images. To this end, a convolutional neural network (CNN) is deployed. The code as well as my comments can be found at my milestone report at the following link: Report_folder.

The rest of this report contains the following sections:

- Problem Description: In this section, I will define the problem, point out the potential client, and describe they can benefit from this project.
- Dataset Description: In this section, I will give the link to the dataset, and point out some important files within this dataset.
- Data Wrangling and Observations: In this section, I will give details about data wrangling using morphology operations, plot graph for each step, and talk about the sacrifices I made due to the lack of computational power of my computer.

- Learning Method: In this section, I will briefly overview CNN method, and demonstrate the structure I used for this network.
- Result and Performance: In this section, I will describe the performance of the method, as well as what one can infer from the result.
- Future Works: In this section I will talk about the potential ways to improve the performance of this project.
- Conclusion: In this section I will close this report by summarizing the project.

2 Problem Description

2.1 Problem Definition

The capstone 2 project comes from the kaggle competition "Data Science Bowl 2017" at the following link: https://www.kaggle.com/c/data-science-bowl-2017. The challenge for this year is detecting lung tumors. More specifically, "Participants will develop algorithms that accurately determine when lesions in the lungs are cancerous, using a data set of thousands of high-resolution lung scans provided by the National Cancer Institute." The scans are provided in the format of CT images.

Given the above description, it is clear that for this project, the objective is:

- Build a model that will detect whether a lung cancer occurred.

2.2 Potential Benefit for Client

According to the project description,

"This will dramatically reduce the false positive rate that plagues the current detection technology, get patients earlier access to life-saving interventions, and give radiologists more time to spend with their patients."

Because of that, potential clients for this project could be hospitals and governmental health/cancer departments.

3 Dataset Description

The data can be found at the kaggle competition site: https://www.kaggle.com/c/data-science-bowl-2017/data.

Main files include:

- stage1.7z: This file contains all the CT images for training stage. Total number of patient is close to 1500. Total size of these files is 150 GB.
- stage1_labels.csv: This file contains the cancer label for each patient, two fields here are patient ID and cancer positive/negative

- stage2.7z: This file contains all the CT images for testing stage. Total number of patient is around 500. Total size for these files is 117 GB.

All CT images come in DICOM format.

For images related to a single patient, it usually comes in a number of slices. Each slice is a vertical view of the 3D image, and in different height. The size of each image is 512 by 512 pixels, and the number of slices for a single patient is around 200. The operations we are going to perform in data wrangling are all slice basis, meaning we apply them in one slice, and move on to the next slice.

4 Data Wrangling and Observations

This section describes the data wrangling part. Since medical imaging is unstructured data, and we plan to use convolutional neural network in this project, we cannot really perform inferential statistics in this project. So I plan to visualize this part as clear as possible.

4.1 Data Preparation

DICOM format does not only save the image. It contains other information supporting medical usage, such as pixel size, patient information, HU scaling.

The images are in different scales. So the first and most important task is transforming all images into standard CT measurement: the Hounsfield Unit (HU). HU measures radiodensity. The steps for the transformation is:

- Fill in the missing data out of CT scanning scope by assuming everything there is air.
- Read scaling slope and intercept, then transform the image into HU measurements

4.2 Morphology Operations

After all images are transformed into HU, it is now time to segment the nodes within the lung. We use morphology operations for this task. It is performed on every slice. It involves in six steps. I am also going to take a slice from stage 1 as an example and visualize the whole procedure.

- Convert the image into a binary image
- Remove the blobs connected to the border of the image.
- Label the image, and keep the labels with 2 largest areas (right lung and left lung)
- Erosion operation with a disk of radius 2 to separate the lung nodules attached to the blood vessels.

- Closure operation with a disk of radius 12 to keep nodules attached to the lung wall.
- Fill in the holes inside the binary mask of lungs

The figure for each step including the original slice and the superimposition by the final mask is shown here 1:

After all the steps, the overall 3D plot looks like this figure 2:

It looks like large nodes in the lung is successfully segmented. Looks good!

4.3 Sacrifices

Before we pass the slices to CNN, there are three major sacrifices I make given my limitations on this project. I will list them in small subsections and explain them one by one.

4.3.1 Downsampling

Since the images are so large, it has to be downsampled given I only have 4GB RAM on my GPU. For each patient, the image is downsampled into 50 pixels by 50 pixels by 20 slices. The slices are evenly selected for the downsampling. This operation can surely cause problems for detecting any tumor with a diameter less than 6mm, because it may not appear on the downsampled image at all.

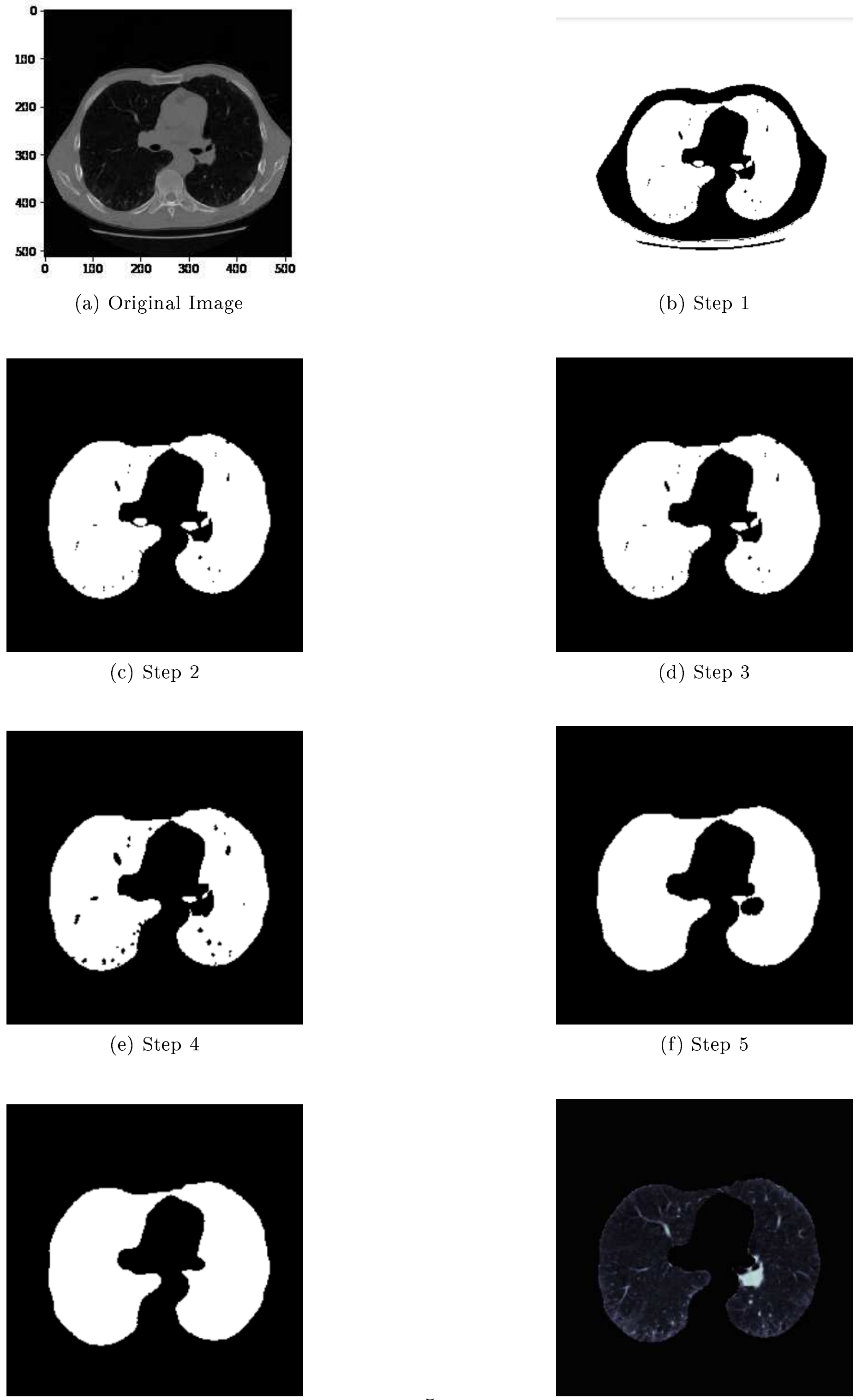
4.3.2 No Further Node Segment

Node segmentation is usually an alternative method for the downsampling. It means further segmenting the nodes from the morphology result, making them into small figures, and then pass it along to neural network. In this way, algorithms can still detect small tumors, and do not have to handle the whole images at once. This is usually the standard procedure in medical image processing, but I do not perform it here.

The reason for me to skip this procedure and use downsampling is that you have to know if each segmented node is cancer or not in order to successfully train the neural network. The top finish for this competition manually labeled every node in the training set. Due to time limitations, I did not perform manual labeling. But this is will be a task for future work, in order to improve performance.

4.3.3 Not training on full training set

There are 1500 patients in the training set, and I only used around 240 of them to train the neural network. The reason for it is again the time limitation. In my estimation, it takes 5 days to apply the morphology operations on full training sets. Since I have to perform the operations on each patient on the testing set (stage 2), I cut down the training set in order to finish the project in time. In the future, after I finish the springboard course, I will run the training on all the patients in the training set and update this report.



(a) Original Image

(b) Step 1

(c) Step 2

(d) Step 3

(e) Step 4

(f) Step 5

(g) Step 6

(h) Superimposition

Figure 1: The morphology steps

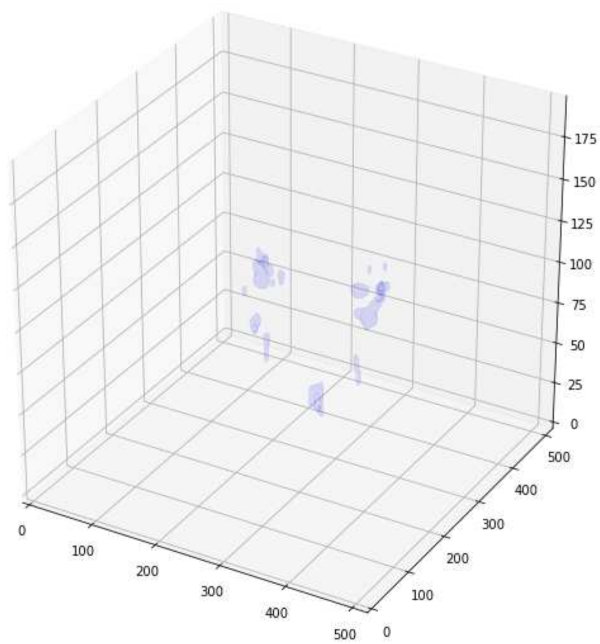


Figure 2: 3D plot for one patient

5 Learning Method: Convolutional Neural Network

After morphology operations, the images are down-sampled and sent to convolutional neural network (CNN). CNN is getting more and more attention in deep learning, and is considered as the weapon of choice when dealing with recognition/classification task on images.

When it comes to recognition/classification tasks in image processing, traditionally people look for features that best describes the characteristic of the image, and then the task becomes a traditional machine learning problem that can be solved by classic ML methods such as SVM or decision trees. For example, given pictures of rocks and eggs, the best way to distinguish egg is to find smooth curves for the boundaries. Traditionally, people find curves or other kinds of shapes by designing a small image chunk (kernel) based on the shape he/she is looking for, and perform convolution multiplication using this kernel to find the particular shape in the image.

The idea for convolutional neural network is quite simple: Instead of deciding the features ourselves, we let neural network decides the best set of features for us. From the algorithm point of view, that means instead of designing the kernels for particular shapes, let the algorithm decide the kernels based on training data.

A typical CNN usually includes multiple convolution layers (conv layers in my figure), each layer contains multiple random initialized kernels and the training data is passed multiple times for the network to decide the best kernels to characterize the classification target. Stacking multiple layers help to catch all characteristic from small to large scale (meaning it can catch shapes like circle and the curves on the circle at the same time).

It also includes maxpool layers to down-sample the outcome from previous layers and prevent the algorithm from overfitting. Finally, multiple fully connected normal neural network layers are used to give the classification result.

5.1 CNN Structure

The structure I used for this project is shown in the following figure:

It uses four convolutional layers to fully capture the characteristics in the image from small to large scale, and then use 3 fully connected normal neural network layers to output the result. I also put maxpool layers between convolutional layers. I also put one dropout layer in the very last to prevent overfitting.

6 Results and Performance

The result consistently passes the benchmark set for the competition, but only 1 out of 4 times will it get close to a bronze model. On average, it ranked around 220 out of 394 teams.

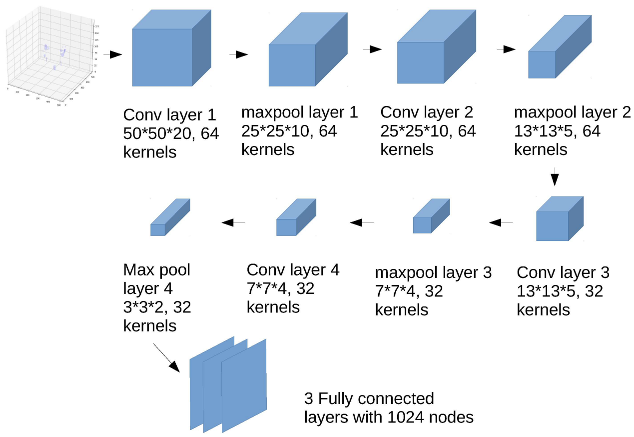


Figure 3: CNN structure

We do not know true label for the images in stage 2. Therefore we cannot know for sure how our algorithm performs. One thing for sure is that it definitely overfits. I observe several times during the training period where the loss on training set drops to zero (indicating serious overfitting). On the other hand, given the cancer rate in the training set is around 30%, it is quite possible that the true cancer rate in the testing set is 30% as well. Compared to that, the 10% cancer rate given by our CNN algorithm suggests we missed a lot of cancer cases, either because of overfitting, or because of the loss of small tumors caused by the downsampling.

7 Future works

The future work definitely contains two points I mentioned in the "Sacrifice" subsection. They are:

- Train the CNN using all the training set instead of 1/5 of them and see if the performance improves.
- Manually label the nodes in the training set, perform node segmentation and train and change CNN structure according to the single node images.

8 Conclusion

In this project, A CNN algorithm is deployed in order to address the problem raised by the "Data Science Bowl 2017" kaggle competition. The performance beats the benchmark for the competition, but it does not excel for a variety of reasons. These reasons are listed in the future works and will be addressed when I have spare time.