CNN based Lung Indexing Method for DICOM CT Image

Chulwoong Choi
Chonnam National University
Gwangju, South Korea
sentilemon02@gmail.com

Sungwoong Yeom
Chonnam National University
Gwangju, South Korea
yeomsw0421@gmail.com

Hieyong Jeong
Chonnam National University
Gwangju, South Korea
h.jeong@jnu.ac.kr

Kyungbaek Kim
Chonnam National University
Gwangju, South Korea
kyungbaekkim@jun.ac.kr

ABSTRACT

PET-CT medical images are widely used for the purpose of early diagnosis of cancer. PET-CT Imaging is a method of examing cancer by photographing the entire body and a larget set of DICOM images are generated for one patient such as 300 images. Since each major doctors focus on different area among this large set of images, automatic indexing method for the focused area is required. In this paper, we propose a CNN-based Lung Indexing Method that can index the image where the lung starts and the image where the lung ends among the whole body DICOM images. The indexed result and the actual answer were compared by using Intersection over Union (IoU). It is confirmed that the accuracy becomes highest at 70% when the start and end index numbers were extracted by using the proposed method with the median value option.

CCS CONCEPTS

• **Computing methodologies** → Visual content-based indexing and retrieval;

KEYWORDS

DICOM, image indexing, deep learning, CNN

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1 INTRODUCTION

DICOM (Digital Imaging and Communications in Medicine, DICOM) is a medical digital imaging and communication standard, such as CT, PET, PET-CT, etc [6]. DICOM images enable more diverse and precise analysis than clinical data. Numerous studies [3][2][5][1] such as rendering and analysis using DICOM lung images have been conducted. 3D rendering of DICOM lung images can detect lung nodules [3]. By segmenting the DICOM lung image, the tumor in the lung can be rendered as a 3D image and the size and shape of the tumor can be observed[2]. DICOM lung images can detect lung cancer using neural networks[5]. In particular, there is a limit to the patient's clinical data when analyzing lung cancer survival. Lung cancer survival analysis should comprehensively analyze clinical data and DICOM images(CT, PET-CT) [1].

In order to use DICOM CT images, a pre-process of extracting only the lungs is required. The doctor can distinguish the lungs on DICOM images in a short time. However, it is difficult for non-medical personnel to extract the lungs while visually checking the DICOM CT image. Even doctors need a lot of time and effort to label DICOM images to differentiate the lungs of all patients.

This paper proposes a CNN-based lung indexing method that can index the start and end images of the lungs in DICOM CT images using deep learning. Create a CNN model that classifies lung start and end images in a patient's full-body DICOM image and learn the model using labeled data (lung start and end images). The CNN model predicts lung start and end images and indexes them using median values. Indexing results and actual DICOM lung images were evaluated by comparison using the Intersection over Union(IoU).

2 RELATED WORK

2.1 DICOM

DICOM CT images use X-rays to take a cross-section of the human body in a short time and identify the location of bones and body structures. DICOM PET-CT images determine the size and location of the tumor based on the degree of response to light through a contrast medium. Basically, DICOM CT image is 512x512 width and height. There are about 300 DICOM images per adult patient. DICOM CT index 0 is the patient's head and moves to the lower half as the index number increases. Meta data information of DICOM CT image such as Slice Thickness, Central Position, Pixel Spacing, and Diameter is also provided as a header [7].

2.2 Convolutional Neural Networks

Deep learning model CNN finds patterns in images and classifies images using patterns. The model is composed of a convolution layer that performs convolution operation using a filter, a max-pooling layer that reduces output data or emphasizes specific data,

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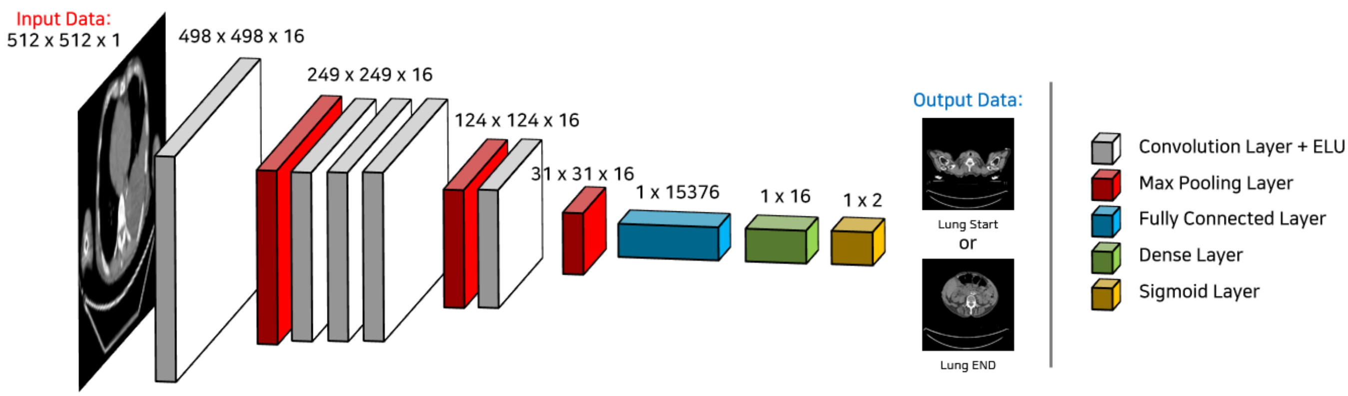

Figure 1: The architecture of the CNN model for classifying the lung start and end images.

and a fully connected layer and a dense layer. Representative CNN models include AlexNe t[4], GoogLeNet [9], and ImageNet [8] who won the ImageNet Challenge.

3 CNN BASED LUNG INDEXING METHOD

3.1 Using Dataset

Table 1 is a dataset used to train and test a CNN-based lung indexing model. The dataset consists of 300 patients with lung cancer provided by Hwasun Chonnam National University Hospital, 374 patients with lung cancer provided by CANCER IMAGING ARCHIVE.

Table 1: Dataset used for learning and experimentation

Dataset	patients
Chonnam National University Hwasun Hospital	300
CANCER IMAGING ARCHIVE	374

3.2 Description CNN Model

The CNN model that classifies the lung start and lung ends is composed of 11 layers. The lung start image and lung end image of 574 patients are used for learning. The total number of learning images is 1148. The CNN model is trained through the 11 layers in Figure 1. DICOM Image (512x512) received as input is convolutional layer and Max-Pooling Layer to reduce convolutional operation and images to find patterns. When passing through the 3rd Max-Pooling Layer, flatten is used to transform the image array value into one dimension. The value transformed into one dimension passes through the Fully Connected Layer and Dense Layer. Finally, the Sigmoid Layer predicts and outputs the probability of the lung start image and the lung end image.

3.3 CNN Model prediction result

The trained model is used to predict the beginning and end of the lung on the DICOM CT image of a lung cancer patient. Figure 2 and Figure 3 are the results of predicting the lung start image and lung end image from the DICOM CT image of the lung cancer patient(LC00040). The x-axis is the index number of the DICOM image. The y-axis is the predicted probability value of the Lung start image or Lung end image.

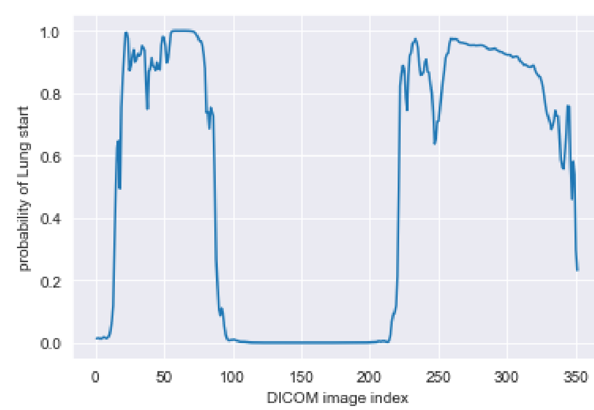

Figure 2: Lung start indexing of DICOM CT Images on Patient(LC00040)

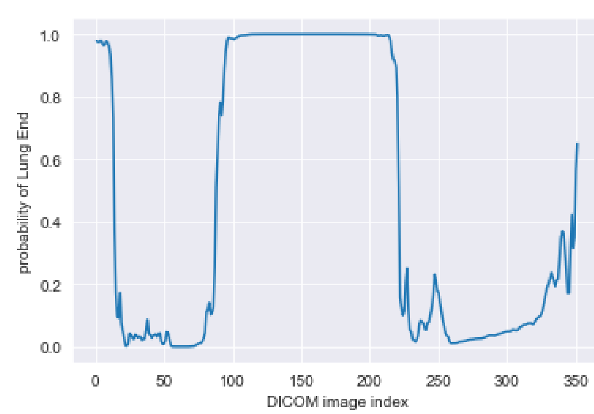

Figure 3: Lung end indexing of DICOM CT Images on Patient(LC00040)

Figure. 2 In the graph, the image between 55 and 70 was predicted as an image of the start of the lung with a 99% probability. Also, Images 220 to 260 are predicted as lung starting images with a high probability. The reason is thought to be that the image of the shoulder where the collarbone ends, defined as the beginning of the lung, and the image of the abdomen and both hands of the patient's lower body are very similar.

Figure 3 In the graph, the image between 110 and 200 was predicted as an image of the end of the lung with a 99% probability. The 90 images were classified as the ends of the lungs, which is thought to be because the ends of the lungs and CT images of the abdomen are very similar.

The trained CNN Model predicts a large number of images as lung start and lung end images. Also, images that are not related to the lungs are classified with high probability. There is a need for a method of accurately finding the lung start image index and the lung end image index.

3.4 Lung Indexing Method Process

This chapter describes how to index the start and end images of the lungs from DICOM CT images based on the CNN Model. Figure 4 represents the overall process.

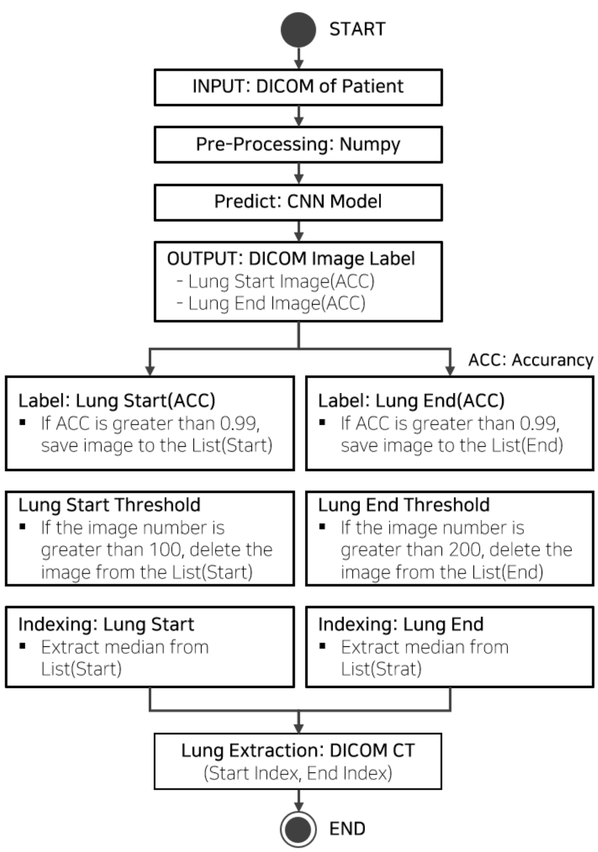

Figure 4: Process of suggested Lung indexing method

3.4.1 INPUT: Dicom of Patient. Import and input DICOM CT images of lung cancer patients.

3.4.2 Pre-Processing : Numpy. Converts DICOM images to arrays using the Numpy library and performs preprocessing such as type conversion and normalization.

3.4.3 Predict: CNN Model and OUTPUT : DICOM Image Label. Using the learned CNN model, the probability of the lung start image and lung end image of the preprocessed DICOM image is calculated.

3.4.4 Label : Lung Start and End. The index numbers of images with higher accuracy than 0.99 are stored in the lung start image list and the lung end image list.

3.4.5 Threshold : Lung Start and End. Images with a lung starting image number greater than 100 and a lung starting image number greater than 200 are removed as they are less relevant to the lung.

3.4.6 Indexing : Lung Start. The median index is extracted from the list of start image and end image.

3.4.7 Lung Extraction : DICOM CT.. The DICOM image is sliced through the extracted index number.

4 EVALUATION

The test is performed using DICOM CT images of 50 patients at Hwasun Chonnam National University Hospital. Measure performance using Intersection Over Union (IoU). Table 2 shows the results of comparing the actual lung images and the lung images sliced with the index extracted through the model proposed in this paper through IoU. The test was performed by changing the index number extraction method from the lung start image list and lung end image list predicted by CNN Model. The performance was good when the median and average were used.

Table 2: Performance Measurement Results Using Intersection Over Union(IoU)

Median Index	Mean Index	Start Index	End Index
0.70	0.69	0.4	0.51

5 CONCLUSIONS

In this paper, a CNN-based Lung Index Method is proposed so that non-medical personnel can easily extract only the lungs from DICOM CT images. When DICOM CT images were indexed as median values from the lung start image list and lung end image list classified in the CNN Model, it was extracted similarly to the actual lung area. However, an IoU value of 0.7 is not very good performance. And There are many improvements, such as the problem of classifying multiple images or classifying parts not related to the lungs in the CNN Model.

In future research, we will improve the performance of the proposed model through DICOM image preprocessing and CNN model modification.

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