



COVID-19 Classification And Lesion Localization From Chest CT

¹ Mrs.T.Sujatha ² Mr. M. Kannan

^{1,2}Assistant Professor

^{1,2}Department of Computer Science,

^{1,2}SRM Arts and Science College, Chennai, Sathyabama University

ABSTRACT—Accurate and rapid diagnosis of COVID-19 suspected cases plays a crucial role in timely quarantine and medical treatment. Developing a deep learning-based model for automatic COVID-19 diagnosis on chest CT is helpful to counter the outbreak of SARS-CoV-2. A weakly supervised deep learning framework was developed using 3D CT volumes for COVID-19 classification and lesion localization. For each patient, the lung region was segmented using a pre-trained U Net; then the segmented 3D lung region was fed into a 3D deep neural network to predict the probability of COVID-19 infectious; the COVID-19 lesions are localized by combining the activation regions in the classification network and the unsupervised connected components.

keywords—COVID-19, CT, deep learning, weak label, SARS-CoV-2, DeCoVNet.

INTRODUCTION

SINCE Dec 2019, a large and increasing outbreak of a novel coronavirus was reported in Wuhan, Hubei province of China [1], [2], which can cause acute respiratory illness and even fatal acute respiratory distress syndrome (ARDS) [3]. The new coronavirus was named as SARS-CoV-2 by International Committee on Taxonomy of Viruses (ICTV) [4] and the infectious diseases infected by this coronavirus was named as Coronavirus Disease 2019 (COVID-19) by World Health Organization (WHO) [5]. The new coronavirus has been confirmed of human-to-human transmission [6], [7], and due to the massive transportation and large population mobility before the Chinese Spring Festival, this new coronavirus has spread fast to other areas in China with considerable morbidity and mortality. According to the data from the National Health Commission of the People's Republic of China [8], update till 24 o'clock of Mar 29, 2020, China has reported 82447 identified cases with SARS-CoV-2, including 3,311 death cases; 82.2% (67,801/82,447) of the identified cases came from Hubei province and identified cases in Wuhan, the very center of epidemic area of Hubei province, accounted about 73.8% (50,006/67,801) of the data in Hubei province. Moreover, COVID-19 cases outside China have been reported in more than 200 countries, areas or territories. Until to 18:00 Central European Time of Mar 29, 2020, a total of 638,146 confirmed cases with 30,039 deaths cases globally was reported according to the COVID-19 situation dashboard in the World Health Organization (WHO) website [9]. Countries with the most numbers of confirmed cases included United States of America with 103,321 cases, Italy with 92,472 cases, China with 82,356 cases, Spain with 72,248 cases, Germany with 52,547 cases, Iran with 38,309 cases, France with 37,145 cases and so on. With the tremendously fast spread of SARS-CoV-2, it has been declared to be a Public Health Emergency of International Concern (PHEIC) by WHO on 30 January 2020 [10], and the global level of assessment of the risk of spread and the risk of impact of COVID-19 has been increased to be Very High by WHO on Feb 28, 2020 [11] which poses a great threat to the international human health. Even though real-time reverse transcriptase

polymerase chain reaction (RT-PCR) has been considered as the gold standard for SARS-CoV-2 diagnosis, the very limited supply and strict requirements for laboratory environment would greatly delay accurate diagnosis of suspected patients, which has posed unprecedented challenges to prevent the spread of the infection, particularly at the center of the epidemic areas. In contrast with it, chest computed tomography (CT) is a faster and easier method for clinical diagnosis of COVID-19 by combining the patient's clinical symptoms and signs with their recent close contact, travel history, and laboratory findings, which can make it possible for quick diagnosis as early as possible in the clinical practice. It is also effectively helpful to isolate infected patients timely and control the epidemic, especially for the severely epidemic areas. In a word, chest CT is a key component of the diagnostic procedure for suspected patients and its CT manifestations have been emphasized in several recent reports.

RELATED WORK

Weakly-supervised object localization is a challenging task in which the object of interest should be localized while learning its appearance. State-of-the-art methods recycle the architecture of a standard CNN by using the activation maps of the last layer for localizing the object. While this approach is simple and works relatively well, object localization relies on different features than classification, thus, a specialized localization mechanism is required during training to improve performance. In this paper, we propose a convolutional, multi-scale spatial localization network that provides accurate localization for the object of interest. Experimental results on CUB-200-2011 and ImageNet datasets show that our proposed approach provides competitive performance for weakly supervised localization. Deep features are important for visual recognition tasks, but deep nets suffer from vanishing/exploding gradients. Also adding more layers results in higher training error (as reported by the results of the experiments in this paper). The proposed ResNet: learn residual functions instead of unreferenced functions.

Supervised learning techniques construct predictive models by learning from a large number of training examples, where each training example has a label indicating its ground-truth output. Though current techniques have achieved great success, it is noteworthy that in many tasks it is difficult to get strong supervision information like fully ground-truth labels due to the high cost of data labeling process. Thus, it is desired for machine learning techniques to work with weak supervision. This article reviews some research progress of weakly supervised learning, focusing on three typical types of weak supervision: incomplete supervision where only a subset of training data are given with labels; inexact supervision where the training data are given with only coarse-grained labels; inaccurate supervision where the given labels are not always ground-truth.

EXISTING SYSTEM

Interactive segmentation often requires image specific learning to deal with large context variations among different images but current neural network are not adaptive to different test images, as parameters of the model are learned from training images and then fixed in the testing stage without image specific adaptation. They proposed a bounding-box-based segmentation pipeline that extracts the foreground from a given region of interest with good compactness to avoid over-fitting.

Proposed System

The Proposed system focus on interactive tumor segmentation of medical image sequences using back propagation neural network. The proposed work utilizes pattern based classification using neural network function. Fuzzy c means clustering is designed in the proposed area. Here the threshold required for segmenting adjusts itself according to the segmented area and position. Finally the classifier is used to check whether the input image is COVID or Non-COVID.

Module Description

Module I: Preprocessing

If the input images are color images means we are convert to gray scale from that color images. In the complement of a binary image, zeros become ones and ones become zeros; black and white are reversed. In the output image, dark areas become lighter and light areas become darker. Images may have different types of noise. In image enhancement, the goal is to accentuate certain image features for subsequent analysis or for image display. Examples include contrast and edge enhancement, pseudo-coloring, noise filtering,

sharpening, and magnifying. Image enhancement is useful in feature extraction, image analysis and an image display. The median filter is used in order to remove the noise from the image. Median filtering is a nonlinear operation often used in image processing to reduce salt and pepper noise. A median filter is more effective than convolution when the goal is to simultaneously reduce noise and preserve edges.

Module II: Segmentation

The image features like color, weight, and depth and pixel information to apply before the classifier. Here we used the fuzzy c means clustering algorithm is used in order to segment the portion of defected areas. Image segmentation is typically used to locate objects and boundaries in images. More precisely image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image.

Module III: Classification

This module is used to establish the neural network concept for training the image and testing the image with the help of weight estimating classifier. The most common type of neural network consists of three groups, or layers, of units: a layer of "**input**" units is connected to a layer of "**hidden**" units, which is connected to a layer of "**output**" units. The activity of the input units represents the raw information that is fed into the network. The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units.

The behavior of the output units depends on the activity of the hidden units and the weights between the hidden and output units. This simple type of network is interesting because the hidden units are free to construct their own representations of the input. The weights between the input and hidden units determine when each hidden unit is active, and so by modifying these weights, a hidden unit can choose what it represents. The result image will compared with the dataset images and it will display whether it is normal or abnormal.

Result & Discussion

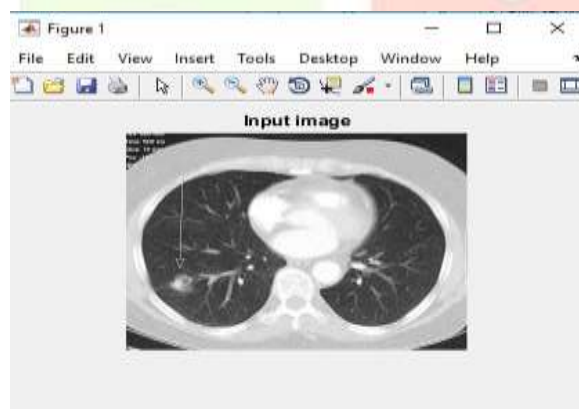


Figure 1.1

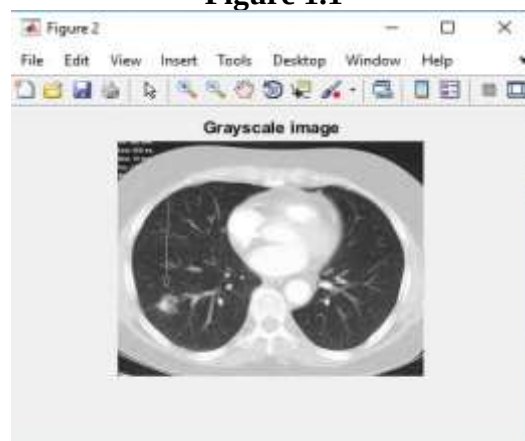


Figure 1.2

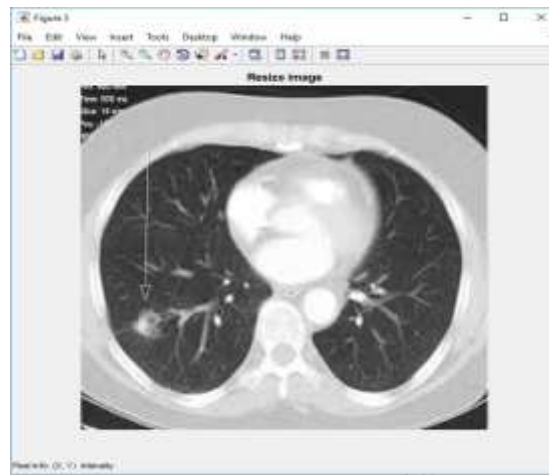


Figure 1.3



Figure 1.4

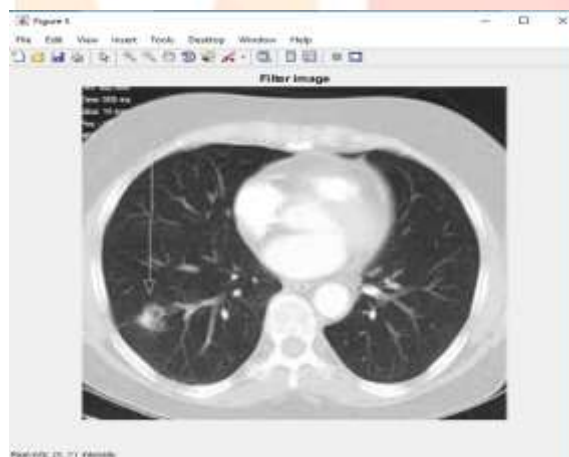


Figure 1.5

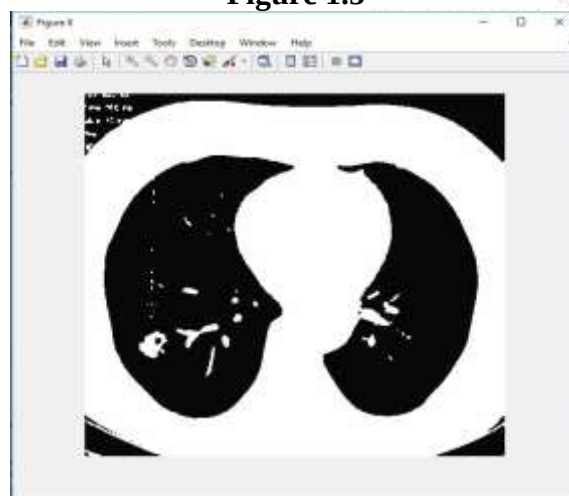


Figure 1.6

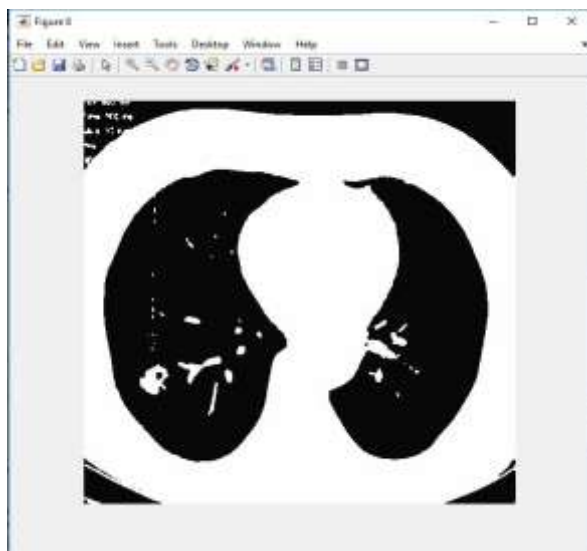


Figure 1.7

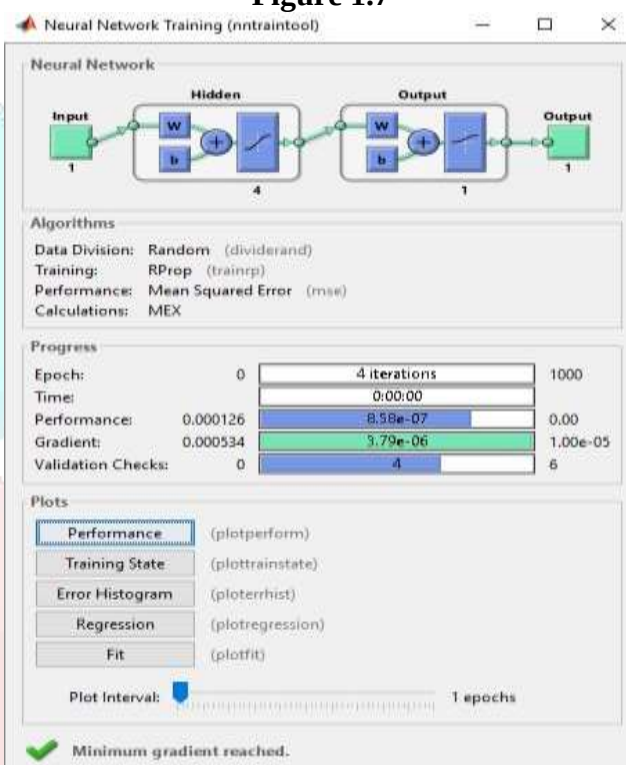


Figure 1.8



Figure 1.9

CONCLUSION

In this paper, we study a general inference framework for extracting lung tumors from medical image sequences. A collaborative formulation of tumor segmentation is discussed by jointly integrating region and boundary information. Here we used the Fuzzy c means clustering algorithm is used in order to segment the portion of defected areas. We used to establish the neural network concept for training the image and testing the image with the help of weight estimating classifier. The result image will compared with the dataset images and it will display whether it is normal or abnormal.

REFERENCES

- [1] C. Huang et al., “Clinical features of patients infected with 2019 Novel Coronavirus in Wuhan, China,” *Lancet*, vol. 395, no. 10223, pp. 497–506, 2020.
- [2] H. Lu, C. W. Stratton, and Y. Tang, “Outbreak of pneumonia of unknown etiology in Wuhan, China: The mystery and the miracle,” *J. Med. Virol.*, vol. 92, no. 4, pp. 401–402, Apr. 2020.
- [3] N. Chen et al., “Epidemiological and clinical characteristics of 99 cases of 2019 Novel Coronavirus pneumonia in wuhan, China: A descriptive study,” *Lancet*, vol. 395, no. 10223, pp. 507–513, Feb. 2020.
- [4] P. Feng et al., “Time course of lung changes on chest CT during recovery from 2019 Novel Coronavirus (COVID-19) pneumonia,” *Radiology*, vol. 295, no. 3, 2020, Art. no. 200370.
- [5] World Health Organization (WHO). Accessed: Feb. 15, 2020. [Online]. Available: https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200213-sitrep-24-covid-19.pdf?sfvrsn=9a7406a4_4
- [6] Q. Li et al., “Early transmission dynamics in Wuhan, China, of novel coronavirus–infected pneumonia,” *New England J. Med.*, 2020.
- [7] J. T. Wu, K. Leung, and G. M. Leung, “Nowcasting and forecasting the potential domestic and international spread of the 2019-nCoV outbreak originating in Wuhan, China: A modelling study,” *Lancet*, vol. 395, no. 10225, pp. 689–697, Feb. 2020.
- [8] (2020). National Health Commission of the People’s Republic of China. Accessed: Feb. 14, 2020. [Online]. Available: <http://www.nhc.gov.cn/xcs/yqtb/202002/553ff43ca29d4fe88f3837d49d6b6ef1.shtml>
- [9] Coronavirus Disease (COVID-19) Situation Dashboard. Accessed: Mar. 30, 2020. [Online]. Available: [https://www.who.int/redirectpages/page/novel-coronavirus-\(covid-19\)-situation-dashboard](https://www.who.int/redirectpages/page/novel-coronavirus-(covid-19)-situation-dashboard).
- [10] World Health Organization (WHO). Accessed: Mar. 30, 2020. [Online]. Available: [https://www.who.int/news-room/detail/30-01-2020-statementon-the-second-meeting-of-the-international-health-regulations-\(2005\)-emergency-committee-regarding-the-outbreak-of-novel-coronavirus-\(2019-ncov\)](https://www.who.int/news-room/detail/30-01-2020-statementon-the-second-meeting-of-the-international-health-regulations-(2005)-emergency-committee-regarding-the-outbreak-of-novel-coronavirus-(2019-ncov))
- [11] D. Ardila et al., “End-to-end lung cancer screening with threedimensional deep learning on low-dose chest computed tomography,” *Nature Med.*, vol. 25, no. 6, pp. 954–961, Jun. 2019.
- [12] W.-J. Guan et al., “Clinical characteristics of 2019 Novel Coronavirus infection in China,” *New England J. Med.*, vol. 382, pp. 1708–1720, 2020.
- [14] F. Song et al., “Emerging 2019 Novel Coronavirus (2019-nCoV) pneumonia,” *Radiology*, vol. 295, no. 1, 2020, Art. no. 200274.
- [15] M. Chung et al., “CT imaging features of 2019 Novel Coronavirus (2019-nCoV),” *Radiology*, vol. 295, no. 1, 2020, Art. no. 200230.