A challenge for detecting chronic pneumonia from chest X-ray images

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Abstract

Purpose:

To detect Japanese pneumonia from clinical chest X-ray images by a machine learning technique based on an open dataset.

Material and Method:

The dataset contains 30227 images manually annotated by radiologists, which was published by RSNA in Aug 2018. We applied YOLOv3 (a real-time object detection system, developed by Joseph Redmon et al, University of Washington) to make use of the dataset. The YOLOv3 model is a single convolutional network that simultaneously predicts multiple bounding boxes and class probabilities for the boxes. We trained this model using the dataset, and detected pneumonia from the clinical X-ray images for Japanese patients.

Background

Death Rates by Cause



The death rate is defined as the number of deaths per 100,000 people. Created by *Nippon.com* based on the Vital Statistics report published in 2018 by the Ministry of Health, Labor, and Welfare





For 30277 chest X-ray images, annotation by 3 radiologists.

Three radiologists indicate the ground glass opacity (GGO) regions in bounding boxes (e.g., a pink rectangle) on the chest X-ray image. The GGO pattern implies a lesion that occurs in pneumonia. The GGO patterns are learned by taking out the textures, densities and edges from the bounding boxes. We prepared 30,224 chest X-ray images that include the GGO lesions annotated in this way by reference to RSNA.

Results:

The results indicate that we can find suspected pneumonia regions and the class-specific confidence score increases with disease condition, suggesting this AI method to be of beneficial. Cancer has been the leading cause of death among Japanese, followed by heart disease and pneumonia since 2010. The elderly people who have lung diseases are increasing, and death rate by pneumonia is increasing as well.

Al-Model based on YOLOv3

	Туре	Filters	Size	Output
	Convolutional	32	3 × 3	256 × 256
	Convolutional	64	3 × 3 / 2	128 × 128
	Convolutional	32	1 × 1	
1×	Convolutional	64	3 × 3	
	Residual			128 × 128
	Convolutional	128	3 × 3 / 2	64 × 64
	Convolutional	64	1 × 1	
2x	Convolutional	128	3 × 3	
	Residual			64 × 64
	Convolutional	256	$3 \times 3 / 2$	32 × 32
	Convolutional	128	1 × 1	
8×	Convolutional	256	3 × 3	
	Residual			32 × 32
	Convolutional	512	3 × 3 / 2	16 × 16
	Convolutional	256	1 × 1	
8×	Convolutional	512	3 × 3	
	Residual			16 × 16
	Convolutional	1024	$3 \times 3 / 2$	8 × 8
	Convolutional	512	1 × 1	
4×	Convolutional	1024	3 × 3	
	Residual			8 × 8
	Avgpool		Global	
	Connected		1000	
	Softmax			



The input image makes the final output layer with an $n \times n$



We iterate the learning procedures up to 15300 times, which takes about 8 hours (about 1h with one Tesla P100 GPU). Then, the feature of 'pneumonia' pattern is acquired as weight. We can use the weight for medical prediction. The prediction for a sample case took 0.1 sec on average.

In normal CNNs, classification of images is performed by a softmax function etc. Contrary, in this model, every layer is constructed by the convolution of so that accurate position information on feature map can be retained. feature map, which corresponds to each grid of the input image divided into $n \times n$ sizes. Each grid has a bounding box with a constant aspect ratio called multiple anchors, which predicts the central coordinate (x, y) (\blacksquare) as anchor and the scale (w, h) of width and height (\Box) . Each anchor box has also a parameter called confidence, which represents the probability that an object exists in the box.

Loading weights from /content/darknet/backup/yolov3_15300.weights...Done! /content/darknet/test.jpg: Predicted in 0.091474 seconds. NOTICE: 19% Confidence score

Result: case1 Mendelson syndrome



Mendelson syndrome (70s Female): left image is for the oldest taken in 2006, middle is for one before the latest, right is for the latest. These were detected for the same region.

Result: case2 Interstitial pneumonia



NOTICE: 1%

Interstitial pneumonia (70s male): left image was taken at the first visit to our hospital, middle was taken when his breath was difficult, right is for 3days after the middle image.



Conclusion



Many elderly patients in Japan have chronic lung diseases. It is desirable to follow up their conditions. To do this, we have built an AI model that can follow their clinical condition. The IoU score is 0.141, which indicates the same as or better than the performance by radiologists.

201



Cropped images by YOLOv3: left is for cropped about right lung region from the image in 2006, middle and right images are for the same region taken in 2019.





Left is for confidential score . It is increasing after 2019/1/4. Right is for the comparison of confidential score and entropy. Entropy is conventionally used as an index of image complexity. The confidential score is more sensitive to the change. The diagnosis by AI often gives rise to false positives. Our model can accurately indicate abnormalities by the use of confidential scores from the patient's own past X-ray images. The scores reflect the patient's clinical condition more faithfully than conventional indexes.

The present method enables us to provide a personalized medical care system for each patient.

Further investigations would be necessary to optimize this method by combining with other clinical test results.