CardioXNet: Automated Detection for Cardiomegaly Based on Deep Learning

Qiwen Que[1,4], Ze Tang[1,4], Ruoshi Wang[1,4], Zeng Zeng[2,4,5], Jie Wang[3], Matthew Chua[1], Teo Sin Gee[2], Xulei Yang[2], Bharadwaj Veeravalli[3]

***Abstract*— In this paper, we present an automated procedure to determine the presence of cardiomegaly on chest X-ray image based on deep learning. The proposed algorithm CardioXNet uses deep learning methods U-NET and cardiothoracic ratio for diagnosis of cardiomegaly from chest X-rays. U-NET learns the segmentation task from the ground truth data. OpenCV is used to denoise and maintain the precision of region of interest once minor errors occur. Therefore, Cardiothoracic ratio (CTR) is calculated as a criterion to determine cardiomegaly from U-net segmentations. End-to-end Dense-Net neural network is used as baseline. This study has shown that the feasibility of combing deep learning segmentation and medical criterion to automatically recognize heart disease in medical images with high accuracy and agreement with the clinical results.**

***Index Terms*— Heart Disease, Deep Learning, U-NET, Dense-Net, OpenCV, CardioXNet**

Introduction

Cardiomegaly is one of the most common inherited cardiovascular diseases with a prevalence at least 1 in 500 in the general population[1], [2]. It is a symptom of cardiac insufficiency which is a heart's response to a variety of extrinsic and intrinsic stimuli that impose increased biomechanical stresses. While hypertrophy can eventually normalize wall tensions, it is associated with an unfavorable outcomes and threatens affected patients with sudden death or progression to overt heart failure[3].

Recently, there are many researches on biomedical images. In terms of cardiomegaly diagnosis, there are edge detection, local thresholding, histogram analysis, fuzzy logic, rule-based scheme based on the shape and size of chest and heart. For example, Takayuki Ishida et al. [4] developed a computerized scheme based on gray-level histogram analysis and an edge detection technique with feature analysis to determine the CTR. Torres-Robles et al. [5] presented a robust fuzzy classifier to find the features of chest size, and the right and left heart boundaries to measure the heart enlargement. Pranav Rajpurkar et al.[6] developed is a 121-layer convolutional neural network to detect all 14 diseases in the chest. Previous researchers have employed convolutional neural network for segmentation in biomedical tasks. Pim Moeskops et al. [7] proposed automatic segmentation of MR brain images into a number of tissue classes using a convolutional neural network. Mohammad Havaei et al. [8] presented a fully automatic brain tumor segmentation method based on Deep Neural Networks (DNNs). Jelmer M. Wolterink et al. [9] used dilated convolutional neural networks (CNNs) for segmentation of the myocardium and blood pool in cardiovascular MR (CMR) of patients with congenital heart disease (CHD).

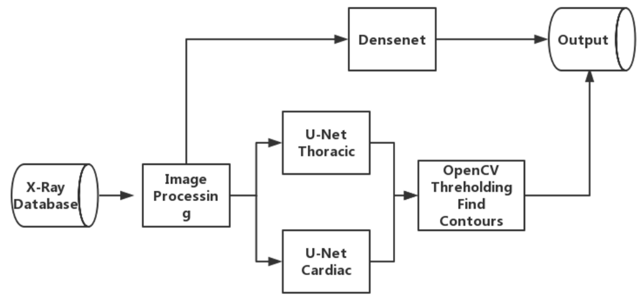

Fig. 1. Pipeline of the proposed method for the task of segmentation

In our paper, we design an innovative method, CardioXNet to diagnose cardiomegaly from chest radiographic images. The integrated architecture of the method proposed is illustrated in fig. 1. X-ray images were used to train U-NET [10] and DenseNet [11]. Typical CNNs aggregate the context by pooling layers. However, CNNs discard the location information of the images. Therefore U-NET was employed to try to instead of typical CNNs for cardiomegaly diagnostics. DenseNet which got the "Best Paper Awards" in CVPR 2017 was used as a baseline approach for image classification.

Methods

Cardiothoracic Ratio

In our paper, the Cardiothoracic Ratio (CTR) was employed as a criterion to determine the cardiomegaly. The cardiothoracic ratio (CTR) on a chest X-ray indicates the relationship between the size of the heart and the size of the chest [12]. Although criticized [13], [14], it is still the routine way for radiologists to detect cardiomegaly. CTR can be identified by measuring eq. 1. R and L are the longest distances from the central vertical line (middle line of the chest) to the right and left heart boundaries,

[1]Institute of Systems Science, National University of Singapore (NUS-ISS), Singapore
[2]Agency for Science, Technology and Research (A*STAR), Singapore
[3]Department of Electrical and ComputerEngineering, National University of Singapore, Singapore
[4]co-first authors
[5]corresponding author

Authorized licensed use limited to: Dalhousie University. Downloaded on December 02,2023 at 17:06:10 UTC from IEEE Xplore. Restrictions apply.

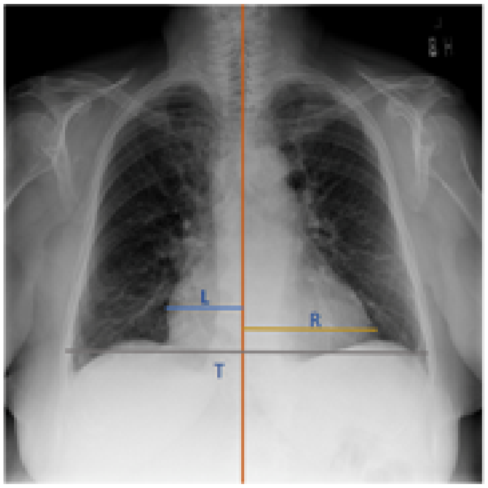

Fig. 2. CTR using maximum cardiac diameter (L + R) and maximum thoracic diameter (T)

respectively, and T is the longest horizontal distance from the left to the right boundary of lung (see fig. 2). The normal cardiothoracic ratio lies between 39% and 50% with an average of about 45%. If the CTR is greater than 0.5, it shows the cardiomegaly in most of cases.

$$CTR = (L + R)/T \tag{1}$$

Segmentation with U-net

To calculate the CTR for detecting whether the patients have cardiomegaly, cardiac diameters and thoracic diameters were supposed to be measured. Compared with typical CNNs, U-Net can save the location information and get high accuracy at the same time[10]. We employed U-Net to get the cardiac and thorax respectively then measured the transverse cardiac diameter (L+R) and maximum internal thoracic diameter (T). It consists of a contracting path (left side) and an expansive path (right side). The contracting path is in accordance with the typical CNN architecture. The contracting path follows the typical architecture of a convolutional. The input images were passed through 3x3 convolutions. ReLU activation function and Dropout with the possibility 0.5 were applied. A 2x2 max pooling operation with stride 2 was used for downsampling. On the expansive path, feature maps from contracting path concatenate 2x2 upsamping layers and same convolution layers.

Dense-Net

Compared with ResNet[15] and Inception[16], Dense-Net alleviates the vanishing-gradient problem, strengthen features propagation, encourage features reuse, and substantially reduce the number of parameters [11].

Dense-Net has L(L+1)/2 direct connections. Each layer has directly access to the gradients from the loss function

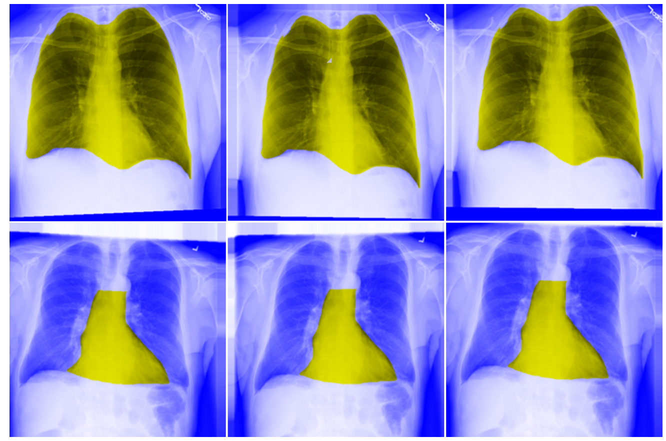

Fig. 3. Examples of merge after augmentation of cardiac and thoracic

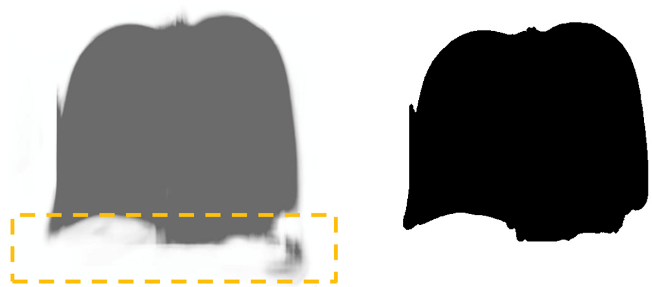

Fig. 4. Example of image denoising

and the original input signals leading to an implicit deep supervision. Dense-Net archives better performances than ResNet with less hyperparameters by using bottleneck layers,

Results

Image Processing

The image dataset was composed by chest X-ray radiographs. We chose 103 standard PA X-ray radiographs from ChestX-ray8 Database released by Wang et al.[17]. The radiographs are transformed to 512x 512 pixels as a training set for the experiment. The dataset was manually labeled for U-NET. For our specific case, the U-NET was assigned two separate tasks, which are 1) obtaining cardiac parts, 2) thoracic parts from X-ray radiographs. Labels were manually cardiac and thoracic segmentation of chest X-ray radiographs. As the limited images we have, the augmentation step was deployed. The X-ray images were augmented by slight rotation, shift, shearing and zooming. The volume of images has reached 2630. The augmentation examples are shown in fig. 3.

Segmentation

The input images were transformed to 512x512 pixels for training U-NET. U-NET was trained with parameters of

Authorized licensed use limited to: Dalhousie University. Downloaded on December 02,2023 at 17:06:10 UTC from IEEE Xplore. Restrictions apply.

TABLE I
U-net Training Results

Label	Accuracy	Loss	Validation	Val Loss Acc
Cardiac	99.26%	0.0580	97.62%	0.1651
Thoracic	95.51%	0.2724	94.96%	0.2856

learning rate: 10^{-4}, batch size: 4, epoch: 10. Final model metrics are shown in tbl. I. The training accuracy of cardiac is 99.26%, validation accuracy is 97.62% and for thoracic, training accuracy is 95.61%, validation accuracy is 94.96%.

After automatic segmentation by U-NET, cardiac and thoracic were generated respectively as the outputs of models. Notice that there were some noises in the output images. In order to prevent subtle errors or noises occurred by segmentation from interfering with the CTR measurement, the cardiac and thoracic obtained by U-NET were processed by OpenCV. The specific processing steps are listed below:

1. RGB cardiac and thoracic images were transformed into binary images.
2. All contours of binary cardiac and thoracic images were acquired by OpenCV.
3. The contour with largest area was kept.
4. The transverse cardiac diameter (L+R) and maximum internal thoracic diameter (T) were measured using contour with largest area.
5. CTR ratio was calculated from transverse cardiac diameter (L+R) and maximum internal thoracic diameter (T).

The result after processed as shown in fig. 4. The useless information in yellow dotted box would be removed in this phase

Comparison

For the architecture of DenseNet, final three layers were retrained and the rest layers are frozen. The batch size was set as 6, the learning rate is given as 10^{-4}. Initial number of filters was 64 and reduction factor of transition blocks was 0.5. The training set and test set used in U-NET are the same within DenseNet.

The cardiac and thoracic were generated from X-ray radiographs by U-NET, maximum transverse diameter of the heart and the maximum width of the thorax were measured by the width of largest contour of the segmentation, and then CTR ratio were calculated. The CTR threshold was set at 0.5 for determine cardiomegaly. The results of accuracy, sensitivity, precision and F-score with DenseNet as baseline are revealed in tbl. II. The AUROC on the test set of CardioXNet is 0.9348 which has slight improvement compared with the CheXNet[6] on the cardiomegaly detection.

TABLE II
DenseNet Training Results

Models	Accuracy	Precision	Recall	F-score	AUC
CardioXNet	93.75%	100%	89.29%	94.34%	0.9348
Dense-Net	87.50%	81.48%	95.65%	88.00%	0.8783

CardioXNet performed better than Dense-Net in detecting cardiomegaly. By deriving cardiac and thoracic features from U-NET and calculating CTR ratio as in eq. 1, we could achieve confusion matrices[18], [19] that accuracy is 93.75%, F1 score is 94.43%, which was better than our Dense-Net base line approach (tbl. II). As precision reached to 100%, all patients who get cardiomegaly were detected completely by our method.

Conclusion

CardioXNet was deployed to conduct cardiomegaly detection. The accuracy of CardioXNet relies on the manual labels, hence it is quite important to prepare precise labels before training. CardioXNet should be able to achieve even better result, if more accuracy manual labels could be acquired from professional radiologists. CardioXNet showed high segmentation accuracy and performed well in recognition of the cardiac and thoracic, even when the patients' dataset was not large enough. By combing CTR as diagnostic metric, our automatic measurement, CardioXNet could achieve 93.75% accuracy, 100% precision, 89.29% recall and 94.34% F-score.

X-ray is only a 2D section of the 3D heart structure[20], whereas, in clinical practices, there are other advanced diagnostic methods such as Electrocardiogram, Echocardiogram (Doppler echocardiography), Cardiac computerized tomography (CT) or magnetic resonance imaging (MRI), which would provide extra information about how efficiently the heart is pumping and determine which chambers of the heart are enlarged [21], [22]. However, X-ray equipment is still the easiest access medical devices for screening cardiomegaly. As the accuracy and consistency with clinical diagnosis, CardioXNet, Our automatic diagnosis algorithm for cardiomegaly would have opportunities to replace manual screen drawing measurement and save millions of hours for radiologists in the future.

Future Work

Firstly, We will put more efforts on enhancing the quality of the manual labels in CardioXNet, which will make CardioXNet have even better performance. Secondly, we will try to make CardioXNet more automatic and user-friendly, which will make CardioXNet more reliable, cost-effective and easier to adopt. Further more, we will expand the diagnosis panel to other lung diseases.

Authorized licensed use limited to: Dalhousie University. Downloaded on December 02,2023 at 17:06:10 UTC from IEEE Xplore. Restrictions apply.

ACKNOWLEDGEMENT

The work was supported by Singapore-China NRF - NSFC Grant [No. NRF2016NRF-NSFC001-111].

References

[1] C. Semsarian, J. Ingles, M. S. Maron, and B. J. Maron, “New perspectives on the prevalence of hypertrophic cardiomyopathy,” *Journal of the American College of Cardiology*, vol. 65, no. 12, pp. 1249–1254, 2015.

[2] B. J. Maron, J. M. Gardin, J. M. Flack, S. S. Gidding, T. T. Kurosaki, and D. E. Bild, “Prevalence of hypertrophic cardiomyopathy in a general population of young adults: Echocardiographic analysis of 4111 subjects in the cardia study,” *Circulation*, vol. 92, no. 4, pp. 785–789, 1995.

[3] N. Frey and E. Olson, “Cardiac hypertrophy: The good, the bad, and the ugly,” *Annual Review of Physiology*, vol. 65, no. 1, pp. 45–79, 2003.

[4] K. C. Takayuki Ishida Shigehiko Katsuragawa, “Computer-aided diagnosis for detection of cardiomegaly in digital chest radiographs,” *Proc.SPIE*, vol. 5747. pp. 5747–5747–7, 2005.

[5] F. Torres-Robles, A. J. Rosales-Silva, F. J. Gallegos-Funes, and I. Bazán-Trujillo, “A robust neuro-fuzzy classifier for the detection of cardiomegaly in digital chest radiographies,” *Dyna*, vol. 81, no. 186, pp. 35–41, 2014.

[6] P. Rajpurkar, J. Irvin, K. Zhu, B. Yang, H. Mehta, T. Duan, D. Ding, A. Bagul, C. Langlotz, K. Shpanskaya, M. P. Lungren, and A. Y. Ng, “CheXNet: Radiologist-level pneumonia detection on chest x-rays with deep learning,” *CoRR*, vol. abs/1711.05225, 2017.

[7] P. Moeskops, M. A. Viergever, A. M. Mendrik, L. S. de Vries, M. J. N. L. Benders, and I. Išgum, “Automatic segmentation of mr brain images with a convolutional neural network,” *IEEE Transactions on Medical Imaging*, vol. 35, no. 5, pp. 1252–1261, May 2016.

[8] M. Havaei, A. Davy, D. Warde-Farley, A. Biard, A. Courville, Y. Bengio, C. Pal, P.-M. Jodoin, and H. Larochelle, “Brain tumor segmentation with deep neural networks,” *Medical image analysis*, vol. 35, pp. 18–31, 2017.

[9] J. M. Wolterink, T. Leiner, M. A. Viergever, and I. Išgum, “Dilated convolutional neural networks for cardiovascular mr segmentation in congenital heart disease,” in *Reconstruction, segmentation, and analysis of medical images*, Springer, 2016, pp. 95–102.

[10] O. Ronneberger, P. Fischer, and T. Brox, “U-net: Convolutional networks for biomedical image segmentation,” in *International conference on medical image computing and computer-assisted intervention*, 2015, pp. 234–241.

[11] G. Huang, Z. Liu, and K. Q. Weinberger, “Densely connected convolutional networks,” *CoRR*, vol. abs/1608.06993, 2016.

[12] C. Danzer, “The cardiothoracic ratio,” *The American Journal of the Medical Sciences*, vol. 157, pp. 513–554, 1919.

[13] J. Davis, M. L. Murphy, L. R. Blue, and E. J. Ferris, “A comparison of objective measurements on the chest roentgenogram as screening tests for right or left ventricular hypertrophy,” *The American Journal of Cardiology*, vol. 58, no. 7, pp. 658–660, 1986.

[14] M. Murphy, L. Blue, P. Thenabadu, J. Phillips, and E. Ferris, “The reliability of the routine chest roentgenogram for determination of heart size based on specific ventricular chamber evaluation at postmortem,” *Investigative radiology*, vol. 20, no. 1, p. 21—25, 1985.

[15] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” *CoRR*, vol. abs/1512.03385, 2015.

[16] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, A. Rabinovich, and others, “Going deeper with convolutions,” 2015.

[17] X. Wang, Y. Peng, L. Lu, Z. Lu, M. Bagheri, and R. M. Summers, “ChestX-ray8: Hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases,” *CoRR*, vol. abs/1705.02315, 2017.

[18] A. D. Forbes, “Classification-algorithm evaluation: Five performance measures based onconfusion matrices,” *Journal of Clinical Monitoring*, vol. 11, no. 3, pp. 189–206, 1995.

[19] X. Deng, Q. Liu, Y. Deng, and S. Mahadevan, “An improved method to construct basic probability assignment based on the confusion matrix for classification problem,” *Information Sciences*, vol. 340, pp. 250–261, 2016.

[20] P. Henzler, V. Rasche, T. Ropinski, and T. Ritschel, “Single-image tomography: 3D volumes from 2D x-rays,” *arXiv preprint arXiv:1710.04867*, 2017.

[21] A. H. Ellims, H. Pfluger, M. Elsik, M. J. Butler, J. L. Hare, and A. J. Taylor, “Utility of cardiac magnetic resonance imaging, echocardiography and electrocardiography for the prediction of clinical response and long-term survival following cardiac resynchronisation therapy,” *The international journal of cardiovascular imaging*, vol. 29, no. 6, pp. 1303–1311, 2013.

[22] T. Kenny T., “Electrocardiogram (ecg),” *Electrocardiogram*, vol. 6, pp. 1–2, 2012.

Authorized licensed use limited to: Dalhousie University. Downloaded on December 02,2023 at 17:06:10 UTC from IEEE Xplore. Restrictions apply.