Automatic Detection of Cardiac Ejection Rate in Left Ventricular Photography Using Deep Learning

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***Abstract*—Left ventricular angiography is an assessment of cardiac structure and function that is often performed during cardiac catheterization. In addition to obtaining the index of left ventricular ejection rate (LVEF), left ventricular angiography also assists in the interpretation of cardiac hypertrophy, valve regurgitation, and regional myocardial systolic dysfunction. This also assists the clinician in the treatment and the judgment of opening the blood vessels. Although left ventricular angiography has been a well-established and internationally recognized detection method, it is not easy to train cardiac catheterization professionals, as image analysis requires sufficient experience but it is time-consuming. In this study, the deep learning models are introduced to reduce clinical interpretation errors and provide information on cardiac function and local cardiac systolic abnormalities in a short period. Then, clinicians can easily make medical decisions and judgments. The models in this study are expected to reduce 90% of operation time and improve the accuracy from 50% to 99%. It also helps detect myocardial hypoxia and determine whether to perform coronary surgery. Automatic and accurate detection of cardiac ejection rate, cardiac hypertrophy1, and abnormal local contraction is enabled to immediately warn and feedback to clinicians to make the most accurate treatment decisions.**

Keywords—Left ventricular ejection fraction (LVEF), cardiac catheterization, Unet, Ellipse method, image segmentation

I. INTRODUCTION

Cardiovascular disease (CVD) is one of the highest rank mortalities around the world. From previous studies [1], CVD is strongly considered to associate with Ejection Fraction (EF). Left ventricular ejection fraction (LVEF) [2] is a central measure of left ventricular systolic function. 50 to 70% of the patients have a normal Left ventricular ejection fraction (LVEF). LVEF is recognized by the process of Transthoracic Echocardiography [3]. The disadvantage is that it needs to take a long time for interpretation and determination.

It is not easy to train recruits, and there is often the possibility of misinterpretation. For example, the accuracy rate of manual interpretation calculated by an experienced cardiologist is around 80%. It may take 10 min to interpret one catheter. If there are 6 catheters one day, it takes an hour to interpret. For new physicians, the accuracy rate of manual interpretation is only 50%, and it may take 30 min to interpret one catheter, and 3 h is needed to interpret 6 catheters a day.

Therefore, deep learning for imaging is an efficient way to improve accuracy and accelerate the process. In addition, previous research focused on the Transthoracic Echocardiography mechanism, but this study focuses on the

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mechanism of cardiac catheterization instead.

II. METHOD

The overall method of this study is shown in Fig. 1. After we obtain the cardiac catheterization data from Chi Mei Hospital (IRB number: CMMC11011-006), we use the TK-Snap software to label the outline of cardiac images and perform two pre-processing steps, namely non-rigid registration and CLAHE. Next, we use VGG-Unet for cardiac segmentation training and testing and dice coefficient to evaluate the results and perform three calculations with the least square method, extreme left to the extreme right, and ellipse method. Finally, we figured out the left ventricular ejection fraction by plugging the segmentation model and the long axis into the formula and compare with the results marked in the physician's clinic evaluated by mean square error, root means square error, and relative error.

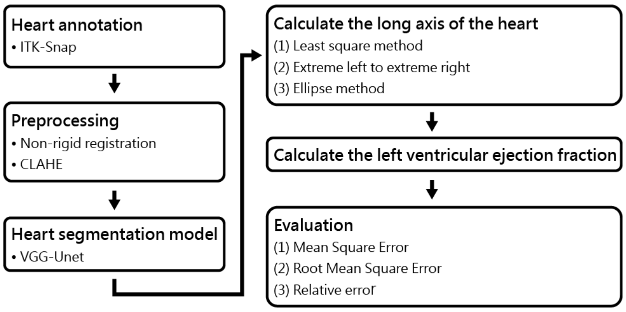

Fig. 1. Workflow of reasearch.

A. Heart annotation:

In this study, medical doctors labeled the circle marks for End Diastolic Volume (EDV) and End Systolic Volume (ESV) as Fig. 2. To make each image suitable for machine learning models, we turned the image as shown in Fig. 3 with a red outline and highlighted area. A total of 42 cases are marked, 28 cases are trained, and 14 cases are tested.

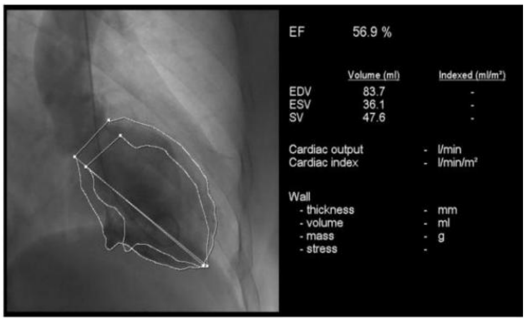

Fig. 2. Labeled image with EF, EDV, ESV,SV by physician.

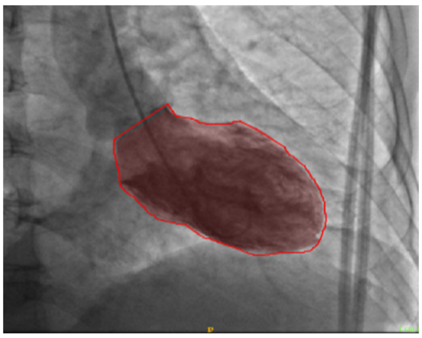

Fig. 3. Relabeled image with red outlines and highlighted area using the polygon function of the ITK-Snap software.

B. Preprocessing

There are two methods for the preprocess of segmentation. The first method is non-rigid registration to normalize images and simulate the condition of a real medical image influenced by patient position or individual position difference [4]. The second method is Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance the contrast of each component of the x-ray image. It is a method to overcome the limitations of global approaches by performing local contrast enhancement [5]. In this study, the method is used to set the threshold of the histogram distribution, and the distribution that exceeds the threshold is evenly dispersed to the probability density distribution, thereby limiting the increase of the transfer function.

C. Heart segmentation model

U-Net is a convolutional neural network developed for biomedical image segmentation by the Computer Science Department of the University of Freiburg. The network is based on a fully convolutional network and its architecture was modified and extended to fewer training images to yield more precise segmentation [6].

U-net, as shown in Fig. 4, is a fully convolutional neural network architecture to extract features. By using upsampling and concatenation, the features of the upper layer are compared with the features of the lower layer at the same time. Therefore, the models grasp the characteristics of objects in detail, the overall situation is also shown and the location of objects is identified accordingly [7]. In this study, we introduced VGG-16-UNet which was related to object segmentation (semantic segmentation) to segment the heart region and generate an image of the cut-out heart. The VGG16-UNet architecture is from a U-Net model with the VGG-16 encoder.

Unet is a classification method for the pixel level of an image. With this, object segmentation is made by pixel classification and used to evaluate by dice coefficient.

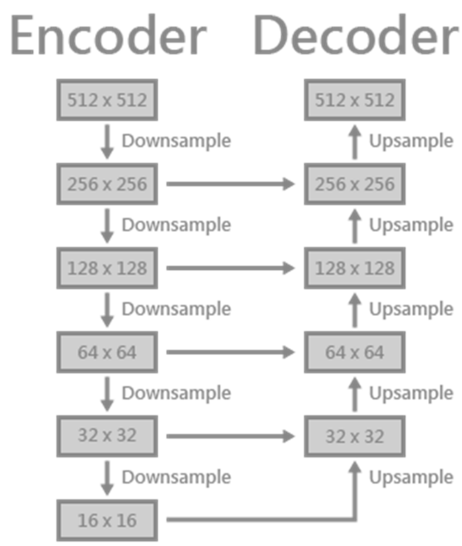

Fig. 4. U-NET Downsampling/Upsampling architecture.

We used three calculation methods, as shown in Fig. 5 for the left ventricular area calculation.

MinAreaRect is to find a rectangle that fits the mask by taking the longest line as the long axis of the heart. Extreme points are found among the leftmost, rightmost, top, and bottom points. The leftmost point is connected to the rightmost, and the top point is to the bottom point. The longest line is taken as the long axis of the heart. Ellipse is found to fit the mask in the openCV library by taking the longest line as the long axis of the heart.

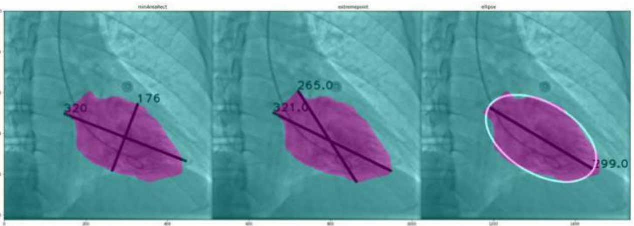

Fig. 5. Three methods of calculation (a) Least square method (b) Extreme left to extreme right (c) Ellipse method

D. Left ventricular ejection rate

We calculated the maximum diastolic and minimum systolic areas of the left ventricle according to the number of pixels in the image generated by the cardiac segmentation model. The equation to obtain the left ventricular ejection rate is added then. The volume is calculated as Eq. (1). A represents areas of the left ventricle, L represents the long axis of the heart. Ejection Fraction (EF), shown as formula (2), is calculated by the End Diastolic Volume (EDV) and End Systolic Volume (ESV).

$$Volume = \frac{8}{3\pi}\cdot\frac{A^2}{L} V = \frac{8}{3\pi}\frac{A^2}{L} \qquad (1)$$

$$\mathrm{EF} = \frac{(\mathrm{EDV - ESV})}{EDV} \quad EF = \frac{EDV-ESV}{EDV} \qquad (2)$$

III. Result

The left-side of Fig. 6. shows the segmentation results obtained directly using U-net. Figure 7. shows the statistical result of the dice score, which indicates the mean dice is 0.879. The range of [0.90–0.95] has the highest chance of appearing.

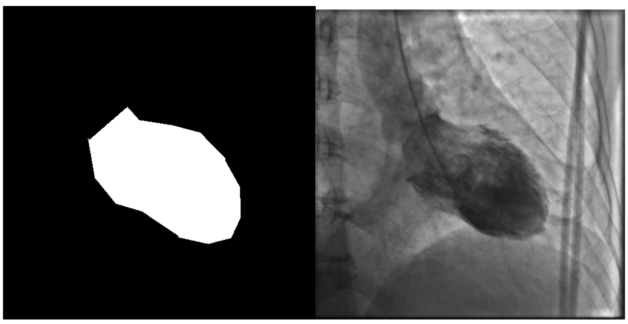

Fig 6. Rresults after segmentation.

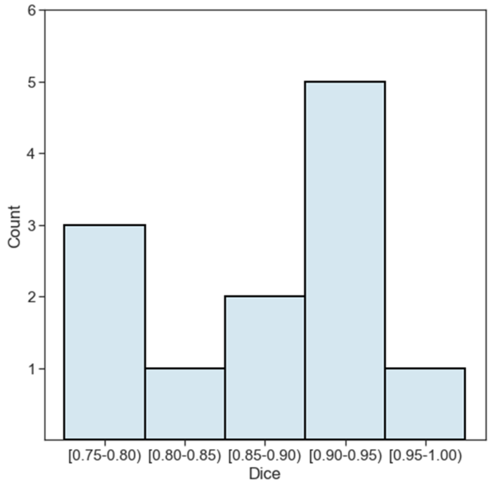

Fig. 7. Dice coefficient of the testing dataset.

After calculating the area of the heart by segmentation models and the state of cardiac contraction in each time series, the change in the area of heart contraction is shown in Fig. 8. The normal heart has regular area changes.

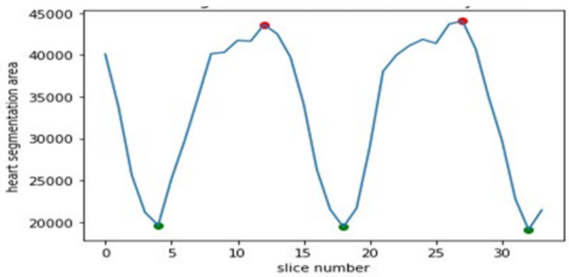

Fig. 8. Change in the area of heart contraction

Finally, after comparing with the injection rate provided by the physician, Fig. 9 shows the statistical results of three different calculation methods including MSE, RMSE, and relative error. The ellipse method is the best among the calculation methods. The MSE of the ellipse method is 0.0052, the RMSE of the ellipse method is 0.055, and the relative error of the ellipse method is 0.069.

TABLE I. Result of different methods

	MSE	RMSE	Relative Error
MinAreaRec	0.0055	0.062	0.087
Extremepoint	0.0064	0.070	0.085
Ellipse	0.0052	0.055	0.069

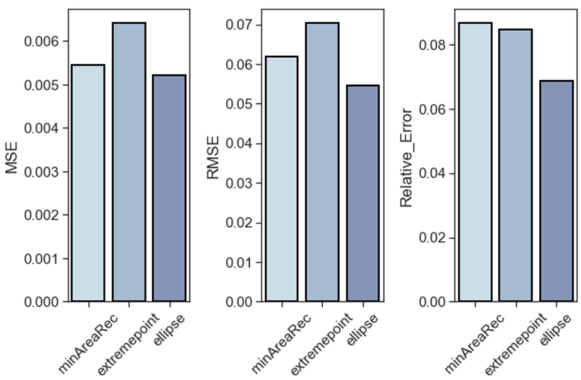

Fig. 9. Comparison of three different calculation methods for three statistical validation index: MSE, RMSE and Relative _Error.

IV. DISCUSSIONS

We compare the error of EF ejection rate with the calculation of different long axes. The ellipse method has the smallest relative error between EF and the physician's interpretation. The main reason is that the ellipse method is closer to the long axis defined by the marked outline. As a result, it is found that this segmentation method is useful, and training is still converging. To improve results, more cases need to be added, and the segmentation edge of labels needs to be fixed. In terms of labeling limitations, the underfilling of the contrast medium sometimes affects the accuracy of the segmentation model. Thus, it is necessary to effectively judge the classification model of the contrast medium and determine whether it is full to calculate the area for better accuracy.

In the future, the AI model can be integrated into the existing cardiac catheterization system by using API to achieve immediate warning, determine whether the heart has signs of heart failure, and assist clinical staff with inefficient interpretation [8].

V. CONCLUSION

In terms of overall accuracy, we suggest greatly improving the accuracy of interpretation. For the benefit of time-saving, interpretation time is shortened to make recommendations. The model provides a good assistant to physicians and radiologists.

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