Automated Left Ventricle Localization from Cardiac MR Images Using Deep Learning

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***Abstract*—Ischaemic heart disease is caused by the blockage of blood flow to the heart and led to an increase in the number of deaths in Malaysia with a total of 18,267 deaths reported in 2018. The use of late gadolinium enhancement (LGE) contrast agents in cardiac magnetic resonance imaging (CMR) for the evaluation of post-MI patients have demonstrated an incremental prognostic value. The LGE allows for direct visualisation of scarred myocardial tissue as a region interest (ROI) that is being enhanced. By assessing the enhanced ROI in the left ventricular (LV), the myocardial scar can be detected and diagnosed. However, the current approach for detecting myocardial scar in LV from CMR images is done visually by the radiologist and is time-consuming and subject to variability. Therefore, it is proposed to incorporate computer-aided diagnosis using a deep learning approach based on the YOLO algorithm for automatically locating the LV region that will improve the diagnostic accuracy of the myocardial scar tissue via LGE data acquired in post-MI patients. In this work, a total of 159 images from 10 subjects are selected and split into three datasets i.e. training, validating and testing datasets with the ratio of 80%, 10% and 10% respectively. The deep learning techniques based on YOLOv2 and YOLOv3 with three different solvers (ADAM, RMSProp and SGDM) are used to evaluate the performance of the automated LV localization from the CMR images. The highest localization accuracy is obtained from YOLOv2 using an ADAM solver with an average precision (AP) of 100% and mean intersection over union (IoU) of 89%.**

***Index Terms*—Cardiac magnetic resonance, Deep learning, Myocardial infarction, YOLO.**

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I. INTRODUCTION

ISCHAEMIC heart diseases remained the major cause of death among Malaysians, with the total number of deaths rising to 18,267 (or 15.6%) in the year 2018 [1]. It is caused by occluded heart arteries in the left ventricle (LV) which supplies oxygen and blood to the heart muscle. When these supplies are completely obstructed, the heart muscle cells die, which give a rise to a heart attack or myocardial infarction (MI) [2], [3]. The MI can be assessed by late gadolinium-enhanced cardiovascular magnetic resonance (LGE-CMR) imaging. However, assessing the severity of the MI is normally performed visually by the experts and consequently a very challenging task that results in a subjective decision based on experts' experience, susceptible to an inaccurate assessment and time-consuming. Therefore, it is necessitated to incorporate computer-aided diagnosis (CAD) and artificial intelligence; i.e. image segmentation and deep learning algorithms which offer an outstanding perspective in improving the diagnostic accuracy and the automation of LGE-CMR image analysis.

For the past decades, various segmentation techniques have been proposed for LV detection or localization, varying from thresholding, boundary detection, statistical models, deformable active contour, level-set approach, and 3D active appearance models [4], [5]. The level-set techniques are computationally intensive for LGE-CMR data and active appearance models are computationally expensive since it needs to have a whole phase of the cardiac cycle as the learning set of data (i.e., images). Works in [6], [7] have implemented Yolo (You Only Look Once) for acquiring the region of interest (ROI) i.e., LV. This process eliminates other non-ROI

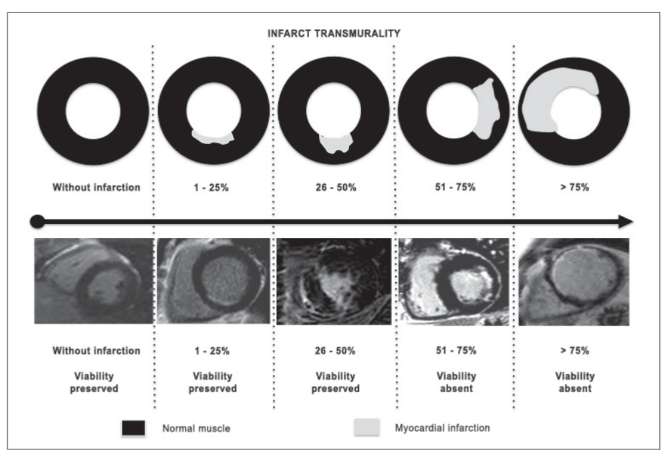

Fig. 1. Examples of different quantification group of LGE implementation on the myocardium [9]

regions from the LGE-CMR images, and thus the segmentation process is robust to irrelevant information.

Nowadays, the use of deep learning in medical image segmentation is increasing rapidly due to the advancement of computing technologies that are capable of performing complex medical image analysis [8]. Deep learning is capable of differentiating the inaccurate boundaries and shape similarity of the LV and other parts of the heart in the presence of noises in images. On top of that, deep learning has shown promising results in image segmentation.

At present, the convolutional neural network (CNN) has been used widely for cardiac image segmentation. The CNN is a supervised machine learning that automatically learns the feature hierarchies and produces robust classification performance. In this research, automated localization of LV from cardiac images using CNN is proposed. The proposed methods consist of four main phases: 1) pre-processing, 2) region of interest (ROI) extraction, 3) training the CNN for segmentation, and 4) post-processing for selecting the targeted region. The rest of the paper is organized as follows. Section II reviews some related literary works. In Section III, the details of our methodology are presented. Finally, section IV is the result and discussion, whereby Section V is the conclusion of this work.

II. Literature Review

MI can be assessed using late gadolinium-enhanced cardiovascular magnetic resonance (LGE-CMR) imaging and it has been established as a standard imaging technique for the assessment of left ventricular (LV) to detect myocardial infarction [9], [10]. The imaging is performed after 10 minutes of gadolinium-enhanced agent injection which over-enhanced the infarcted myocardial region by accumulating in the damaged tissue [11], [12]. Normal myocardium tissue results in fast gadolinium wash in and wash out with no gadolinium-enhanced agent abnormal accumulation is existed. Fig. 1 illustrated the different groups of quantification of the LGE enhancement.

The major constraint of LGE-CMR for the MI assessment is the lack of a clinical standard for myocardial scar tissue quantification. The myocardial scar is evaluated using indices that are based on geometrical measurements of regions of the heart: i.e. the wall thickness of the myocardium, the myocardial mass or the blood pool volume [13], [14]. These indices are typically computed using a labour-intensive segmentation of the delineations of the myocardium and the blood pool. Nevertheless, this process is very time-consuming, demands clinical experience and is susceptible to large inter-rater variability which will influence the measures attained [15].

Nowadays there is no reference procedure for myocardial scar tissue detection and segmentation, even though numerous techniques have been investigated [16]. For these implications, there is an important clinical need to define segmentation methods that are capable of speeding up the process, offering reliability, repeatability, scalability, and fully automatic. In recent years, the advancement of medical image segmentation and deep learning algorithms offer an engrossing perspective for the automation of LGE-CMR image analysis for MI.

A. *Left Ventricle (LV) Segmentation*

Segmentation is one of the fundamental problems in cardiac image analysis and relates to the process of delineating the area of interest in terms of image pixels or voxels [17]. Currently, most of the delineating process is done manually or semi-automatically requiring visual assessment and human interaction, the lesion quantification process turns tedious, subjective and hardly reproducible [9], [18].

Over the years, researchers have implemented various techniques for segmenting the LV, varying from thresholding, boundary detection, statistical models, deformable active contour, level-set approach, etc. [19], [20]. These methods have been proven in attaining good segmentation accuracy on the developed database. However, they are subjected to inferior accuracy, poor robustness, and restricted capability to generalize over patients with LV conditions outside of the training data of the developed database [21]. Even though the segmentation obtained from these registrations may be accurate for the global field of view of the images [22], they may not be accurate for the targeted myocardial scar tissue.

Several perceivable challenges in developing a fully automated segmentation method from LGE-CMR images are the artefacts and the noise in the images, the large inconsistency of the shape of the myocardium, inversion recovery, slice thickness, spatial resolution, and the complexity to choose the most basal slice to segment [23], [24]. To overcome these constraints, researchers have adopted a deep learning technique for developing automated segmentation in cardiac MRI.

B. *Deep Learning*

Image segmentation can be fully automated by utilising the deep learning approach, specifically the convolutional neural network (CNN). The CNN is capable of executing path overlaying for the use of a high number of the atlas which increases the range of anatomy that can be predicted with the developed deep learning model and also accelerates the process [25]–[27]. A work in [28] demonstrates a fully automatic MRI cardiac segmentation using a cardiac centre-of-mass regression module which allows for an automatic shape before registration based on CNN. The results revealed that the segmentation of the left ventricle (LV) and right ventricle (RV) along with the myocardium from a 3D MRI cardiac volume in 0.4 seconds with an average Dice coefficient of 0.90 and an average Hausdorff distance of 10.4 mm.

The advantages of CNN are also presented in [29] for fully automatic segmentation of disease classification using cardiac cine MR images. The CNN has achieved 91% accuracy for assigning the patients to the correct disease category and the segmentation and disease classification only took 5 seconds per patient. Another CNN framework based on 2D and 3D segmentation models is introduced in [30], [31]. The 2D segmentation model is trained slice-by-slice, whereas the 3D model is computed for volumetric segmentation. Even though the CNN methods have shown promising results in this area of research, it still produces anatomically inaccurate segmentations as they provide no guarantee of the anatomical validity of their outcome, even when using a shape prior [26], [32], [33]. Nonetheless, several research works have proposed an improvement in the deep learning architecture by utilising different approaches [26], [34], [35].

The established late gadolinium-enhanced cardiovascular magnetic resonance (LGE-CMR) imaging is a gold standard for assessing myocardial infarction (MI). Nevertheless, current practice in assessing the severity of the MI is performed manually by the cardiologist and thus vulnerable to an inaccurate evaluation. Adopting computer-aided diagnosis and deep learning have been proven with promising results. Over the years, improvement methods for diagnosing the severity of the MI based on automated segmentation and deep learning are developed. However, this advantage comes at a high computational cost. At present, fully-automated scar segmentation is still a challenging task since the infarcted regions in patients can lead to kinematic variabilities and abnormalities in those contrast-enhanced images.

III. METHODOLOGY

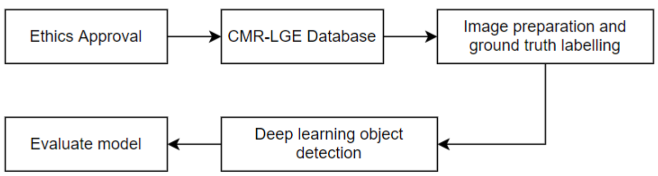

Fig. 2. Block diagram of the object detection using deep learning

This section explains the methodology used to detect LV automatically from LGE-CMR images using CNN-based YOLO object detection. The YOLO stand for You Only Look Once and as the name implies, it performs only a single forward propagation through the CNN for object detecting. Furthermore, the YOLO has advantages in speed of detection, high accuracy detection, and excellent learning capabilities. The overall methodology is shown in Fig. 2.

A. *Ethics Approval and Data Collection*

The proposed study has been registered and approved from Jawatankuasa Etika Penyelidikan Manusia Universiti Sains Malaysia (JEPeM-USM) with assigned study protocol code USM/JEPeM/21090623. The data acquisition stage for this study involves the collection of images of LGE-CMR from post-MI patients which include 2-chamber, 3-chamber, 4-chamber and short-axis images. Images are collected from Picture Archiving and Communication System (PACS) in Imaging Unit, AMDI, USM. The image data was acquired at the Patient Contributed Image Repository in a pixel size of Digital Imaging and Communications in Medicine (DICOM) format. To comply with ethical regulation that has been used, the data is de-identified and anonymised before being transferred to the public domain.

In this work, a publicly available left ventricular (LV) scar dataset from Medical Image Computing and Computer-Assisted Intervention 2012 (MICCAI 2012) [36] is used for the algorithm development. A total of 159 images from 10 subjects were selected before the development of LV detection using deep learning.

B. *Image Preparation and Ground Truth Labelling*

The acquired images from the 10 subjects that are in DICOM format were converted to JPEG using Radiant software with desired 580x580 pixel. The ground truth labelling is performed using the Image Labeller App in MATLAB. This process involves a manually drawn bounding box for locating the LV region as shown in Fig. 3 below. The ground truth data is stored in a two-column table, where the first column comprises the image file paths and the second column contains the LV bounding boxes.

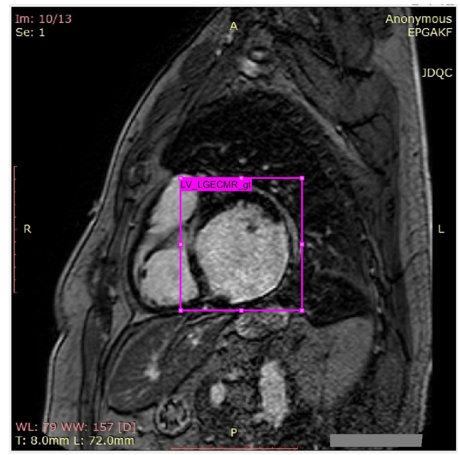

Fig. 3. Example of a bounding box surrounding the region of interest, i.e. LV region

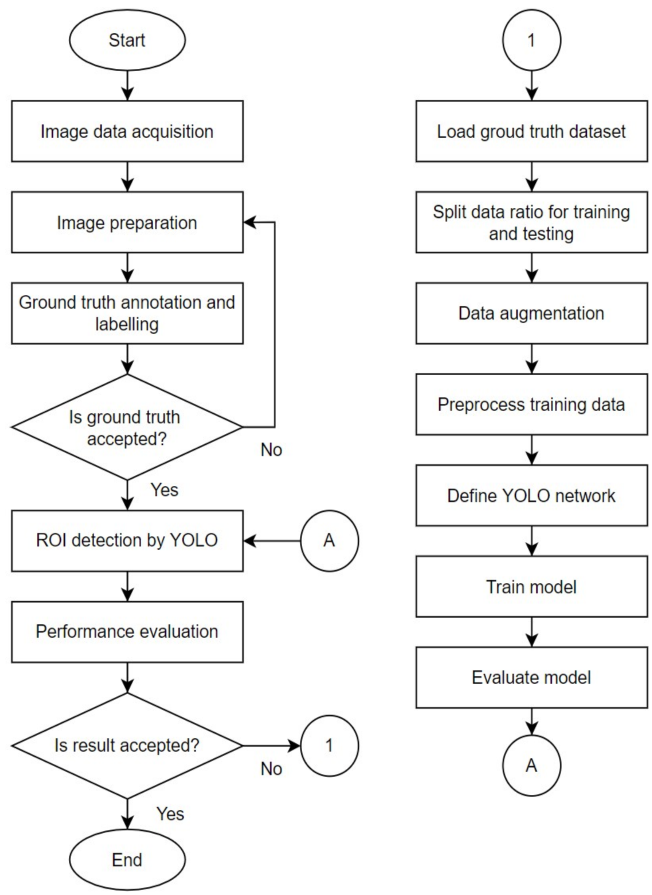

Fig. 4. Flowchart of the YOLO object detection

TABLE I
TRAINING OPTION FOR YOLOV2 AND YOLOV3

Training options	YOLOv2	YOLOv3
Network input size	[224 224 3]	[227 227 3]
Anchor boxes	6	6
Feature extraction network	ResNet-50	SqueezeNet
Solver	SGDM	SGDM
Batch size	16	16
Learning rate	0.001	0.001
Max epoch	30	30

C. *Deep Learning Object Detection*

The deep learning approach is used in this study for automated object detection. The entire process is summarized in the flowchart in Fig. 4.

1) Load ground truth dataset

The developed ground truth dataset is split into three datasets which are training, validation and testing datasets with a ratio of 80%, 10%, and 10% respectively. The training dataset is used for training the network detector, the validation dataset is used for evaluating the performance of the network detector and the testing dataset is used for testing the trained detector.

2) Data Augmentation

Data augmentation is capable of increasing network accuracy by randomly transforming the developed ground truth dataset during the training process. The augmented process applied for this network detection is random horizontal flipping, random X/Y scaling, and jitter image colour (i.e. contrast, hue, saturation, and brightness).

3) Pre-process Training Data

The augmented training dataset and validation dataset are pre-processed by transforming all the images into a specific target size i.e., network input size (as shown in Table 1). There was no image scaling involved in this process. The YOLO was implemented using MATLAB 2020a on a computer with a single GTX 1660 GPU.

4) Define YOLO Network

YOLOv2 is based on ResNet-50 and YOLOv3 is utilized on SqueezeNet for feature extraction. Several input parameters i.e., network input size (the size of the image), number of anchor boxes (set as 6 to achieve a good trade-off between the number of anchors and mean IoU), and number of classes need to be determined before the model training as shown in Table I.

5) Train Model

Subsequently, several important parameters need to be specified for training the model which are a type of solver (e.g., stochastic gradient descent with momentum, SGDM), batch size, initial learning rate, maximum epoch number, etc. The general architecture of the YOLO network based on CNN is shown in Fig. 5.

D. *Evaluate Model*

Average precision (AP), recall and mean intersection over union (IoU) are used for model evaluation. The AP provides a single number that incorporates the ability of the detector to make correct classifications (precision) and the ability of the detector to find all relevant objects (recall). The IoU is an evaluation metric used to measure the accuracy of an object detector on a particular dataset. The AP is the area under the precision-recall curve.

TABLE III
OVERALL PERFORMANCE OF YOLO V3

Dataset	Training the network (%)			Results (%)				
	Training	Validation	Testing	AP	Precision	Recall	Mean IoU	Time (Min)
159	80	10	10	0.94	1	0.5	0.89	25.9

TABLE IV
OVERALL PERFORMANCE OF YOLO V2

Dataset	Training the network (%)			Results (%)				
	Training	Validation	Testing	AP	Precision	Recall	Mean IoU	Time (Min)
159	80	10	10	1	1	0.5	0.89	6.2

TABLE II
OVERALL PERFORMANCE OF YOLO V2 USING DIFFERENT SOLVER

Solver	AP	Precision	Recall	Mean IoU	Training Time (Min)	Threshold	Detection (bbox)
SGDM	1	1	0.5	0.89	6.2	0.5	1
RMSProp	0.98	0.97	0.53	0.89	7.8	0.5	2
ADAM	**1**	**1**	**0.5**	**0.89**	**5.8**	**0.5**	**1**

$$\mathrm{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} \tag{1}$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{2}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{3}$$

Where the TP, TN, FP, and FN refer to the true positives, true negatives, false positives, and false negatives respectively. Apart from the evaluation models mentioned above, the time required for each network to train is also used as a performance indicator.

IV. RESULT AND DISCUSSION

In this work, the performance of deep learning detection for the left ventricle from cardiac MR images is analysed using two techniques which are YOLOv2 and YOLOv3. Tables II and III showed the performance evaluation of YOLOv3 and YOLOv2 respectively.

A. *Performance Comparison of YOLOv3 and YOLOv2*

YOLOv3 has achieved AP and mean IoU of 0.94 and 0.89 respectively and YOLOv2 has achieved AP and mean IoU of 1 and 0.89 respectively. Even though the performance of both YOLO was comparable, the YOLOv2 is chosen as the best object detector based on a shorter network training time of 6.2 minutes compared to YOLOv3 with 25.9 minutes of training time. To improve object detection accuracy in YOLOv2, different solvers i.e. stochastic gradient descent with momentum (SGDM), adaptive moment estimation (ADAM),

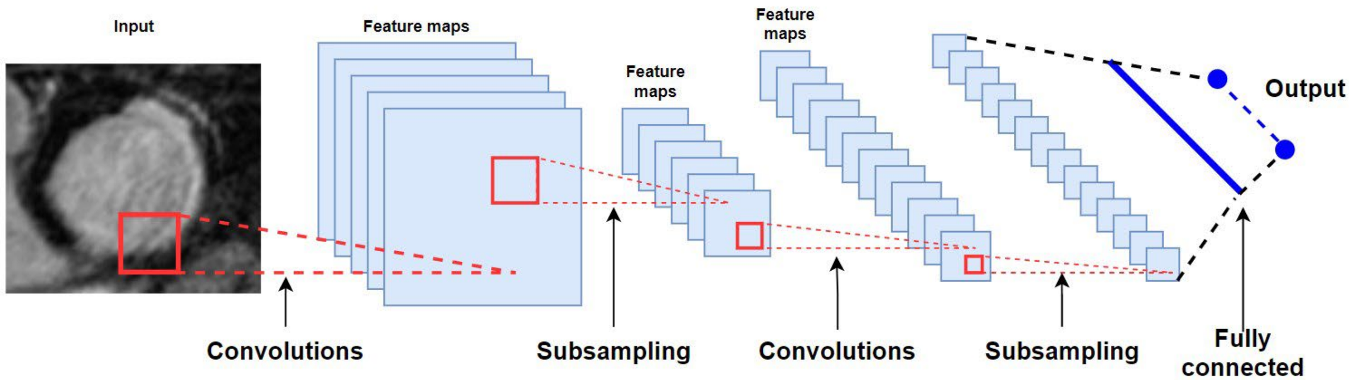

Fig. 2. General architecture of CNN

and root mean square propagation (RMSProp) have been instigated for analysing the performance.

B. *Performance Comparison of Yolo v2 using Different Solver*

The performance comparison of YOLOv2 with different solvers is tabulated in Table IV. YOLOv2 with ADAM solver has achieved the best detection accuracy with AP and mean IoU of 1 and 0.89 with the fastest training time of 5.8 minutes. The threshold is set to 0.5 to ensure object detection that overlaps less than 0.5 with the ground truth images is discarded. The ADAM solver has achieved the best result due to its capability in adapting the parameter learning rates as in RMSProp and utilising the average of the second moments of the gradients as in SGDM [37]–[39].

V. Conclusion

This work aims to locate the LV region automatically for myocardial infarction diagnosis using a deep learning approach. A total of 159 images from 10 subjects are selected and partitioned into training, validating and testing datasets with the ratio of 80%, 10% and 10% respectively. The deep learning techniques based on YOLOv2 and YOLOv3 are implemented to evaluate the performance of automated LV localization from cardiac magnetic resonance (MR) images. The presented results show that the YOLOv2 with ADAM solver is the best architecture to locate the LV region with the AP and mean IoU of 1 and 0.89 respectively. Hence, the outcome from this study hopefully can be considered for use in the CAD systems for automatic detection of myocardial scar in the LV. This study is expected to be further extended into integrating image enhancement and a deep learning approach for left ventricular scar segmentation from cardiac MR images.

Acknowledgement

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