CONVOLUTIONAL NEURAL NETWORK MODEL FOR LEFT VENTRICLE SEGMENTATION TO DETECT MYOCARDIAL INFARCTION

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"In the Name of Allah, the Most Beneficent, the Most Merciful".

"To Almighty Allah, who gave me strength and wisdom to complete this work, Alhamduliaalh".

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ABSTRACT

The quantification of the left ventricle (LV) by cardiac short-axis magnetic resonance images (MRI) is critical in the diagnosis of cardiovascular diseases. The LV clinical metrics are frequently extracted based on the LV segmentation and localization from short-axis MRI images. Manual LV segmentation and localization is tedious and time-consuming task for medical experts to diagnose cardiac pathologies. Therefore, a fully automated LV segmentation and localization technique is required to assist medical experts in working more efficiently. This study proposed a region-based convolutional network (Faster R-CNN) for the localization of LV from short-axis cardiac MRI images using a region proposal network (RPN) integrated with deep feature classification and regression. In addition, a fully convolutional network (FCN) architecture for automatic LV segmentation from short-axis MRI images was proposed. Several experiments were conducted in the training phase to compare the performance of the network and the U-Net model. The segmentation models were trained and tested on a public dataset, namely the evaluation of myocardial infarction from the delayed-enhancement cardiac MRI (EMIDEC) dataset. The dice metric, Jaccard index, sensitivity, and specificity were used to evaluate the segmentation network's performance, with values of 0.93, 0.87, 0.98, and 0.94, respectively. Based on the experimental results, the proposed network outperforms the standard U-Net model and is an advanced fully automated method in terms of segmentation performance. The localization model was effective, with accuracy, precision, recall, and F1 score values of 0.91, 0.94, 0.95, and 0.95, respectively. This model also allows the cropping of the detected area of LV, which is vital to reduce the computational cost and time during segmentation and classification procedures. The proposed methods could be improved to be applicable in clinical practice for doctors to diagnose cardiac diseases from cardiac short-axis MRI images.

ABSTRAK

Pemeriksaan ventrikel kiri (LV) dengan menggunakan Pengimejan Resonan Magnet (MRI) paksi pendek jantung adalah sangat penting dalam mendiagnosis penyakit kardiovaskular. Metriks ventrikel kiri, kebiasaannya diekstrak berdasarkan pembahagian dan pengasingan daripada imej MRI paksi pendek. Pembahagian dan pengasingan LV secara manual adalah tugas yang sukar menyebabkan pakar perubatan memerlukan masa yang panjang untuk mendiagnosis patalogi jantung. Oleh itu, kaedah pembahagian dan pengasingan yang berfungsi sepenuhnya secara automatik adalah diperlukan untuk memastikan kecekapan pakar perubatan dalam menjalankan tugas mereka. Didalam kajian ini, satu rangkaian konvolusi berasaskan kawasan (faster R-CNN) untuk pengasingan LV daripada imej MRI jantung paksi pendek menggunakan rangkaian RPN, disepadukan dengan klasifikasi dan regresi ciri mendalam telah disarankan. Sehubungan itu, satu prototaip rangkaian konvolusi sepenuhnya (FCN) telah dibangunkan. Beberapa eksperimen telah dijalankan sewaktu fasa ujikaji, untuk membandingkan prestasi antara rangkaian tersebut dan model U-net. Model pembahagian telah dijalankan dan diuji keatas sekumpulan data umum iaitu penilaian infarksi miokardium daripada kumpulan data perkembangan jantung terbantut MRI (EMIDEC). Metrik dadu, indeks Jaccard, sensitiviti dan kekhususan telah digunakan untuk menilai prestasi rangkaian pembahagian, masing-masing bernilai 0.93, 0.87, 0.98, dan 0.94. Berdasarkan keputusan eksperimen, rangkaian yang disarankan didapati telah berjaya mengatasi model U-Net standard dan merupakan kaedah automatic sepenuhnya yang lebih canggih dari segi prestasi pembahagian. Kaedah pemisahannya adalah berkesan, dengan benar, tepat, panggilan kembali dan skor F1 masing-masing bernilai 0.91, 0.94, 0.95, and 0.95. Model ini juga berupaya untuk membolehkan pemisahan kawasan LV yang dikesan, yang penting untuk mengurangkan kos pengiraan, masa pembahagian serta prosedur pengelasan. Kaedah yang dicadangkan boleh dipertingkatkan untuk digunakan dalam amalan klinikal untuk doktor mendiagnosis penyakit jantung daripada imej MRI paksi pendek jantung.

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LIST OF SYMBOLS AND ABBREVIATIONS

ACDC	–	Automated Cardiac Diagnosis Challenge
Adam	–	Adaptive moment estimation
AE	–	Auto-encoder
AF	–	Atrial fibrillation
AHA	–	American Heart Association
AMDB	–	Anatomical model database
ANN	–	Artificail neural network
AO	–	Ascending aorta
APD	–	Average perpendicular distance
ASM	–	Active shape model
A4C	–	Apical four-chamber
A2C	–	Apical two-chamber
BN	–	Batch normalization
CAD	–	Coronary artery disease
CAP	–	Cardiac atlas project
CHD	–	Congenital heart disease
CHF	–	Congestive heart failure
CHT	–	Circular Hough transform
CMRI	–	Cardiac magnetic resonance imaging
CNN	–	Convolutional neural network
CPU	–	Central processing unit
CT	–	Computed tomography
CVD	–	Cardiovascular disease
CVRG	–	Cardiovascular research grid
DBN	–	Deep belief network

DCM	–	Dilated cardiomyopathy
DICOM	–	Digital imaging and communications in medicine
DL	–	Deep learning
DM	–	Dice metric
DMTRL	–	Deep multi-task relationship learning network
DNN	–	Deep neural network
DR	–	Diabetic retinopathy
DSC	–	Dice score coefficient
DT	–	Decision tree
ECG	–	Electrocardiogram
ED	–	End-diastole
EF	–	Ejection fraction
EMIDEC	–	Evaluation of myocardial infarction from delayed-enhancement cardiac MRI
ER	–	Error rate
ES	–	End-systole
FCN	–	Fully convolutional network
FD3D	–	Fisher-discriminative 3D
FFNN	–	Feed-forward neural network
FN	–	False negative
FOV	–	Field-of-view
FP	–	False positive
FPGA	–	Field programmable gate array
GAN	–	Generative adversarial network
GM	–	Graph matching
GPU	–	Graphical processing unit
GRU	–	Gated recurrent unit
GUI	–	Graphical user interface
HCM	–	Hypertrophic cardiomyopathy
HED	–	Holistically-nested edge detection
iDASH	–	Integrated data analysis and sharing

IMCA	–	Information maximising component analysis
IOU	–	Intersection over union
KNN	–	K-nearest neighbours
LA	–	Left atrium
LAD	–	Long-axis dimension
LAX	–	Long-axis
LDA	–	Linear discriminant analysis
LGE	–	Late gadolinium enhancement
LSTM	–	Long-short-term-memory
LV	–	Left ventricle
LVEDV	–	Left ventricle end-diastolic volume
LVEF	–	Left ventricle ejection fraction
LVESV	–	Left ventricle end-systolic volume
LVM	–	Left ventricular mass
LVSC	–	Left ventricle segmentation challenge
LVCO	–	Left ventricle cardiac output
LVS	–	Left ventricle strain
LVSV	–	Left ventricular stroke volume
LVV	–	Left ventricular volume
MI	–	Myocardial infarction
MICCAI	–	Medical Image Computing and Computer Assisted Intervention
ML	–	Machine learning
MRI	–	Magnetic resonance imaging
MTL	–	Multi-task learning
NIfTI	–	Neuroimaging Informatics Technology Initiative
NPV	–	Negative predictive value
PA	–	Pulmonary artery
PC	–	Personal computer
PDM	–	Point distribution model
PET	–	Positron emission tomography
PNG	–	Portable network graphics

PPV	–	Positive predictive value
PSNR	–	Peak signal-to-noise ratio
RA	–	Right atrium
RAM	–	Random access memory
R-CNN	–	Region-based convolutional neural network
ReLU	–	Rectified Linear Unit
RFNN	–	Recurrent fuzzy neural networks
RFRS	–	Relief and Rough Set
RMSProp	–	Root Mean Squared Propagation
RNN	–	Recurrent neural network
ROI	–	Region of interest
RPN	–	Region proposal network
RV	–	Right ventricle
RWT	–	Regional wall thicknesses
SAD	–	Short-axis dimension
SAX	–	Short-axis
SCD	–	Sunnybrook cardiac dataset
SGD	–	Stochastic gradient descent
SGDM	–	Stochastic gradient decent momentum
SPECT	–	Single-photon emission computed tomography
SSIM	–	Structural similarity index
SV	–	Stroke volume
SVM	–	Support vector machine
TN	–	True negative
TP	–	True positive
VIP	–	Virtual imaging platform
UCI	–	University of California Irvine
US	–	Ultrasound
WHS	–	Whole heart segmentation

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CHAPTER 1

INTRODUCTION

1.1 Introduction

This chapter introduces the key elements of the research topics. Section 1.2 represents a brief background of the research components, followed by stating the research problems in section 1.3, and the research objectives are listed in section 1.4. The scope and the research contribution are presented in section 1.5 and 1.6, respectively. Finally, the organization of the thesis is explained briefly in section 1.7.

1.2 Research background

Cardiovascular disease (CVD) is regarded as one of the most severe threats to human health, and it has contributed to an increase in the global mortality rate. According to the World Health Organization, 17.9 million people died from cardiovascular disease in 2016, accounting for 31% worldwide deaths [1]. The American Heart Association estimates that human life expectancy can be extended by ten years if cardiovascular diseases can be prevented by effective diagnosis at an early stage. The early detection of CVDs is a crucial factor in determining the suitable treatment that can improve human life and decrease the mortality rate. As a result, there is a growing emphasis on research and technologies that can effectively improve the diagnosis of cardiovascular diseases while also lowering the mortality rate caused by those diseases. In recent years, the diagnosis of cardiovascular diseases has become more accessible thanks to advancements in medical imaging techniques such as computed tomography (CT) and cardiac magnetic resonance imaging (CMRI).

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APPENDIX C

LIST OF PUBLICATIONS, AWARDS AND COPYRIGHTS

Journal Papers:

1. **Shaaf, Z. F**., Jamil, M. M. A., Ambar, R., Alattab, A. A., Yahya, A. A., & Asiri, Y. (2022). Automatic Left Ventricle Segmentation from Short-Axis Cardiac MRI Images Based on Fully Convolutional Neural Network. *Diagnostics*, *12*(2), 414. (**ISI index Q2, IF=3.992**)
2. **Shaaf, Z. F.,** Jamil, M. M. A., & Ambar, R. (2021). A review on left ventricle segmentation and quantification by cardiac magnetic resonance images using convolutional neural networks. *Maejo International Journal Of Science And Technology*, 15(3), 273-292. **(ISI index Q4, IF= 0.636)**
3. **Shaaf, Z. F.,** Jamil, M. M. A., Ambar, R., Alattab, A. A., Yahya, A. A., & Asiri. Detection of Left Ventricular Cavity from Cardiac MRI Images Using Faster R-CNN. *Computers, Materials & Continua*, vol. 74, no.1, pp. 1819–1835, 2023. (**ISI Q2** index, **IF=3.86**)
4. **Shaaf, Z. F.**, Muhammad Mahadi Abdul Jamil, and Radzi Ambar. Deep Learning Approaches to Predict Heart Disease: Overview.(**accepted** by *GRaCe 2020* to be published in *AETiC* journal. (**Scopus** index)
5. **Zakarya Farea Shaaf ,** Muhammad Mahadi Abdul Jamil, and Radzi Ambar. Convolutional Neural Network Model to Segment Myocardial Infarction from MRI Images, (**accepted** in International Journal of Online and Biomedical Engineering, **scopus and WoS index)**

Conference Paper :

1. **Shaaf, Z. F.,** Jamil, M. M. A., & Ambar, R. (2022). Automatic Localization of the Left Ventricle from Short-Axis MR Images Using Circular Hough Transform.

In *Proceedings of the Third International Conference on Trends in Computational and Cognitive Engineering* (pp. 501-508). Springer, Singapore.

2. **Shaaf, Z. F.**, Jamil, M. M. A., & Ambar, R. (2021). Efficient Convolutional Neural Network Model to Segment Left Ventricle from MRI Images. *Multidisciplinary Applied Research and Innovation*, *2*(3), 073-076.
3. **Zakarya Farea Shaaf**, Muhammad Mahadi Abdul Jamil, Radzi Ambar, Mohd Helmy Abd Wahab ;Convolutional Neural Network for Denoising Left Ventricle Magnetic Resonance Images, Computational Intelligence and Machine Learning Approaches in Biomedical Engineering and Health Care Systems (2022): https://doi.org/10.2174/9781681089553122010004.

AWARDS:

1. **Gold** Medal for "Efficient Convolutional Neural Network Model to Segment Left Ventricle from MRI Images" at Innovative Research, Invention and Application Exhibition (I-RIA 2021) July 5, 2021.
2. **Best project** for "Efficient Convolutional Neural Network Model to Segment Left Ventricle from MRI Images" from institute for artificial intelligence and big data (AIBIG) at I-RIA 2021.
3. **Silver** Medal for "Fully Convolutional Neural Network (CNN) Model For Left Ventricle (LV) Segmentation To Detect Myocardial Infarction (MI) Disease" at Virtual International Research and Innovation Symposium and Exposition (RISE2020) November 2020.
4. **Silver** Medal for "Efficient Convolutional Neural Network Model to Segment Left Ventricle from MRI Images" at Virtual International Research and Innovation Symposium and Exposition (RISE2021) 2021.
5. **Gold** Medal for "Convolutional Neural Network Model to Segment myocardial infarction from MRI Images" at Innovative Research, Invention and Application Exhibition (I-RIA 2022) August 9, 2022.

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APPENDIX D

VITA

The author was born on January 1st, 1991 in Dhamar, Yemen. He went to Alfarook and 26 September schools for his High school. He pursued his degree at Universiti Tun Hussein Onn Malaysia (UTHM), Batu Pahat, Johor, Malaysia, and graduated with the B.Eng. (Hons) In Electronic Engineering in 2016. He then enrolled at Universiti Tun Hussein Onn Malaysia, in 2016, where he was awarded the MSc. in Electrical Engineering in 2018. Thereafter, he furthered his Ph.D. program at the Universiti Tun Hussein Onn Malaysia after graduation. Mr. Zakarya Farea Shaaf has authored various papers and achieved medals in areas of cardiac images segmentation using deep learning approaches to diagnose cardiovascular diseases from cardia MRI images.