A Convolutional Neural Network Model to Segment Myocardial Infarction from MRI Images

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Zakarya Farea Shaaf, Muhammad Mahadi Abdul Jamil(✉), Radzi Ambar
Faculty of Electrical and Electronic Engineering,
Universiti Tun Hussein Onn Malaysia, Johor, Malaysia
mahadi@uthm.edu.my

Abstract—Cardiovascular diseases (CVDs) are considered one of the leading causes of death worldwide. Myocardial infarction (MI) is one of the deadliest cardiac diseases that require more consideration. Recently, cardiac magnetic resonance imaging (MRI) has been applied as a standard technique for assessing such diseases. The segmentation of the left ventricle (LV) and myocardium from MRI images is vital in detecting MI disease at its early stages. The automatic segmentation of LV is still challenging due to the complex structures of MRI images, inhomogeneous LV shape and moving organs around the LV, such as the lungs and diaphragm. Thus, this study proposed a convolutional neural network (CNN) model for LV and myocardium segmentation to detect MI. The layers selection and hyper-parameters fine-tuning were applied before the training phase. The model showed robust performance based on the evaluation metrics such as accuracy, sensitivity, specificity, dice score coefficient (DSC), Jaccard index and intersection over union (IOU) with values of 0.86, 0.91, 0.84, 0.81, 0.69 and 0.83, respectively.

Keywords—cardiovascular disease, myocardial infarction, deep learning algorithms, cardiac MRI segmentation, convolutional neural networks

1 Introduction

Cardiovascular diseases (CVDs) are challenging diseases that threaten most people worldwide [1]. Myocardial infarction is a common CVD affecting many patients and increasing the leading causes of death globally [2]. Early detection of MI is crucial for effective diagnosis and therapy to alleviate the MI risk that leads to death. Several techniques have been used for assessing MI include electrocardiogram (ECG) [3]–[5] computed tomography (CT) scan [6], [7] and magnetic resonance imaging (MRI) [8]–[11] In particular, cardiac MRI is the gold standard modality for assessing myocardial tissue providing comprehensive information on the myocardium's structures and functions [12]. Segmentation approaches are widely used in clinical CMR analysis to delineate the healthy and pathological contours of LV and myocardium.

Manual segmentation in clinical routines is time-consuming and subject to intra- and inter-observer variations. Thus, automatic or semi-automatic segmentation methods are highly required. Several traditional segmentation methods have been proposed for cardiac MRI segmentation, including thresholding [13], Gaussian mixture model [14], [15], graph-cut model [16], atlas-based method [17], and active contour models [18]. However, the traditional segmentation algorithms require intervention and expert knowledge to delineate the myocardium and LV borders, which also have poor performance. Thus, automatic segmentation models for myocardium and LV from cardiac MRI images are proposed utilizing deep learning approaches. This paper proposes a CNN model for automatic LV and myocardium segmentation to detect MI areas from late gadolinium enhancement (LGE) short-axis MRI images.

2 Related works

Medical imaging analysis plays a critical role in diagnosing disease such as diabetic retinopathy [19], skin cancer [20] and lung disease [21]. In literature, several studies have been reported for automatic segmentation of myocardial scar and edema. Majority of such works are based on the integration of prior shape information of the myocardium to detect myocardial infarction [9]. Several methods employed traditional segmentation techniques such as thresholding based on image intensity and resolution to distinguish healthy and pathological tissues. Recently, deep learning-based algorithms have achieved state-of-the-art performance of myocardium, and LV segmentation in cardiac MRI [22]–[25], and more recent studies in this field are summarized in [26]. Table 1 summarized the characteristics of the recent related works in LV and myocardium segmentation using deep learning algorithms.

Table 1. Summary of related studies for LV and myocardium segmentation using deep learning techniques (FCN = fully convolutional neural network, DRN = dilated residual network, HPPRN = hybrid pyramid pooling network, LSTM = long short-term memory)

Authors	Technique	Objective	Dataset
Tan *et al*. [27]	CNN regression	LV segmentation	2D Short-axis MRI
Shaaf *et al*. [22]	FCN	LV and myocardium segmentation	2D Short-axis MRI
Du *et al*. [23]	DRN with HPPN	LV and myocardium segmentation	3D Short-axis MRI
Qi *et al*. [24]	CNN	LV and myocardium segmentation	2D Short-axis MRI
Du *et al*. [25]	Encoder-decoder with LSTM	Bi-ventricles segmentation	2D Short-axis MRI
Yang *et al*. [28]	CNN with U-Net	LV segmentation	2D Short-axis MRI

Most of deep learning models for myocardial infarction segmentation focuses on mono-sequence cardiac MRI images, such as LGE. The cardiac images are acquired from different sequence, providing meaningful information of heart function. Automatic LV segmentation from cardiac MRI data remains a challenge in medical image analysis, which plays an effective role in early detection of cardiovascular diseases [29]–[32]. Winther *et al*. [33] proposed deep learning model to determine cardiac mass and function parameters based on biventricular segmentation. Bernard *et al*. [34]

summarized deep learning models for automatic MRI cardiac multi-structure segmentation and diagnosis. They measured the effectiveness of the state-of-the-art deep learning models in segmenting the myocardium and ventricles as well as classifying pathologies. Recently, Pérez-Pelegrí *et al*. [35] proposed a deep learning model based on 3D U-Net to estimate LV volume in the end diastole frame. The proposed method provided explanation for obtaining results in the form of segmentation mask without the need of labels for training. Furthermore, an automatic pipelines for myocardial and scar segmentation from short axis LGE-MRI was proposed by Mamalakis *et al*. [36]. The initial segmentation step is to estimate the myocardial boundaries by applying multi-atlas segmentation techniques. The following step is combining k-mean clustering and a geometric median shape variation techniques to refine myocardial segmentation. Then, an active contour technique was applied to determine healthy and unhealthy myocardial wall. The scar segmentation pipelines in an integration of a Rician–Gaussian mixture and full width at half maximum thresholding models, to define the intensity pixels in scar areas. The last step was segmentation of final scar regions by using watershed model with automatic seed-points framework. Based on limitations in previous proposed models such as inaccurate detection of position and size of endocardial and epicardial regions, and low segmentation accuracy in some patients, an automatic and accurate segmentation models for LV and myocardial segmentation to detect MI are in demand. Therefore, this work proposed a segmentation model that has achieved superior performance for MI segmentation compared with previously proposed methods. The essential step is applying pixel normalization for the training dataset to allow the network to extract features adequately even without extensive images.

3 Methodology

This study proposes a CNN model for myocardial infarction detection based on the segmentation of short-axis MRI images. The procedures for the proposed model are illustrated in Figure 1. The images and their corresponding labels are fed into selected CNN layers. Fine-tuning network hyper-parameters, including optimization algorithm (SGDM), learning rate (0.001), and epochs number (100), is an essential step before the training phase to ensure an efficient performance for the MI area detection.

3.1 Dataset

The image sequence with their corresponding labels used in this work was provided by the EMIDEC segmentation challenge [37]. The EMIDEC dataset consists of 150 exams from LGE-MRI associated with 12 clinical physiology features such as age, gender, history of cardiac diseases, etc. Each subject has different number of images with series of 5–10 short-axis slices for the LV area from base to apex. The corresponding contours of the normal myocardium, LV cavity, and MI are identified and marked by experts with more than 15 years of experience in medical imaging field. Due to the complex structures with the irregular shape of LGE-MRI in the EMIDEC dataset, preprocessing tools such as cropping and normalization were applied to extract region of interest (ROI) features (LV and myocardium) and remove irrelevant anatomical structures. Moreover, data augmentation using rotation and flipping of images was performed to provide adequate training images for the proposed network with promising performance.

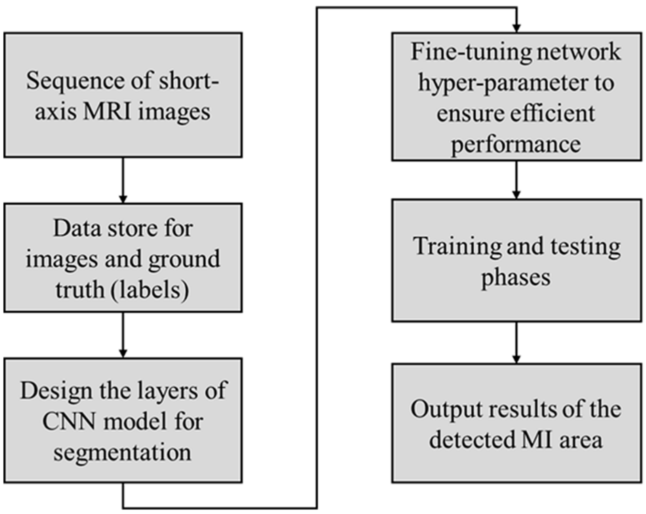

Fig. 1. Procedures of the proposed CNN model

Figure 2 shows the proposed CNN model layers architecture that extracts image features to detect MI areas if they exist in input images. The input layer represents the pixel matrix of the input images. The convolutional layer is the backbone of the CNN building block that consists of learnable filters (kernels) with height and width to learn features throughout the training phase. The convolutional layer is always followed by a rectified linear unit (ReLU) as an activation function that introduces non-linearity into the convolutional layer's output. Max-pooling layer is used to create a down-sampled feature map by calculating the maximum values for patches of feature maps. Transposed convolutional layer, known as the deconvolutional layer, reverses the operation of the standard convolution layer to generate an output feature map and retrieve input dimensions using up sampling. The last layers of the CNN network are the pixel classification layer for semantic image segmentation with outputs of the categorical label for each image pixel and the softmax layer to assign probabilities to each class, respectively.

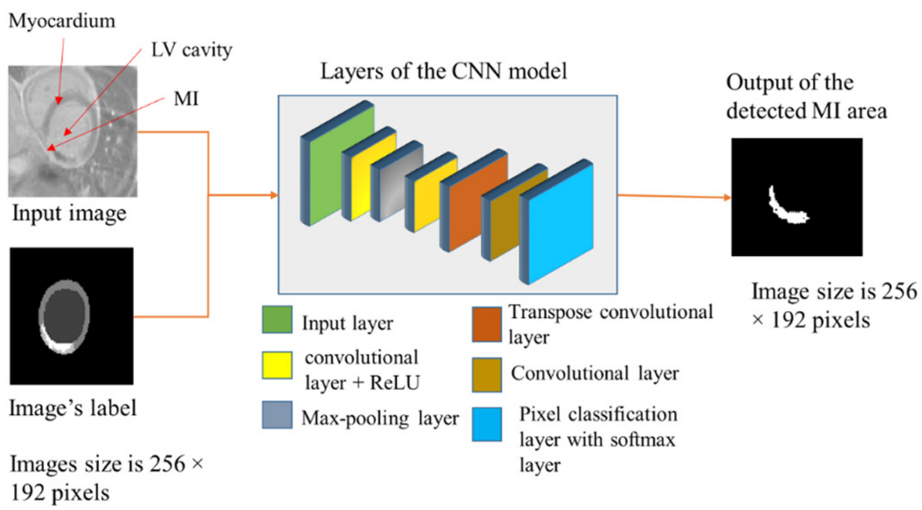

Fig. 2. Architecture layers of the proposed CNN model

3.2 Performance evaluation

The parameters used in the evaluation phase for the proposed network were accuracy, sensitivity, specificity, dice score coefficient, and Jaccard index, as follows:

$$\mathrm{acc} = (\mathrm{TP} + \mathrm{TN})/(\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}) \tag{1}$$

$$\mathrm{sens} = \mathrm{TP}/(\mathrm{TP} + \mathrm{FN}) \tag{2}$$

$$spec = TN/(TN + FP) \tag{3}$$

$$\mathrm{DSC}(\mathrm{A,M}) = 2\left(\frac{|A \cap M|}{|A| + |M|}\right) \tag{4}$$

$$J(A.M) = \frac{A \cap M}{A \cup M} = \frac{A \cap M}{A + M - (A \cap M)} \tag{5}$$

Where *TP* (true positive) represents ROI that is correctly predicted as ROI; *TN* (true negative) represents background area that is correctly detected as background; *FP* (false positive) represents background region that is incorrectly detected as ROI; and *FN* (false negative) represents ROI region that is incorrectly detected as background. *A* represnts the predicted ROI and *M* for manual ROI.

4 Results and discussion

The proposed CNN model was trained and tested using short-axis MRI images for a patient with myocardial infarction. Based on the layers selection and fine-tuning of the selected hyper-parameters, the model performance was robust in detecting MI regions in different cases. Figure 3 depicts the model accuracy and loss function during training phase. The evaluation metrics such as accuracy, sensitivity, specificity, dice score coefficient (DSC), Jaccard index and intersection over union (IOU) are illustrated in Figure 4. The accuracies of the proposed segmentation network are 0.84, 0.87 and 0.86 for LV, myocardium and MI, respectively. The proposed model gained sensitivity with values of (0.71, 073, and 0.91), specificity (0.90, 0.94, and 0.84), DSC (0.74, 0.79, and 0.81), Jaccard index (0.59, 0.65, and 0.69) and IOU (0.55, 0.58, and 0.83) for LV, myocardium, and MI, respectively. The network detection of MI outperformed the detection of LV and normal myocardium (Myo) regions in terms of sensitivity, DSC, Jaccard index and IOU with values of 0.91, 0.81, 0.69 and 0.83, respectively.

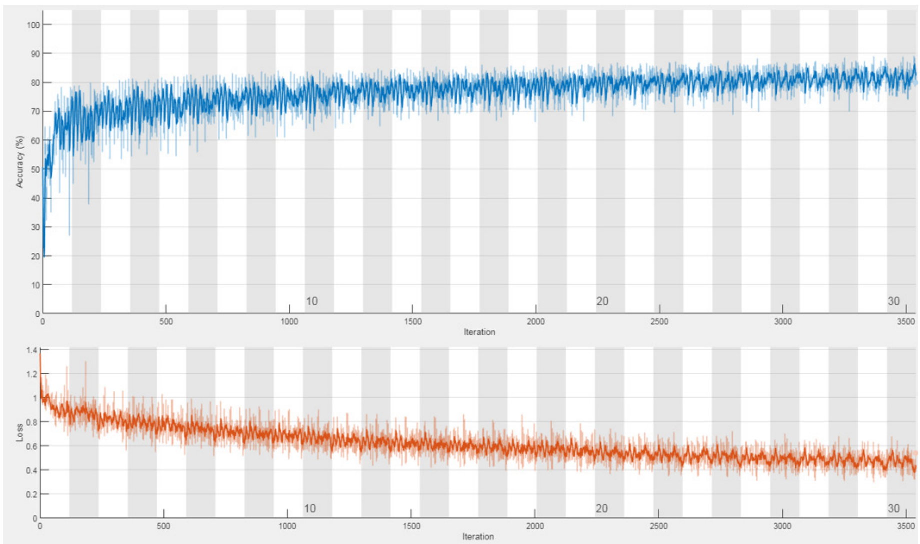

Fig. 3. Training accuracy and loss function of the proposed network

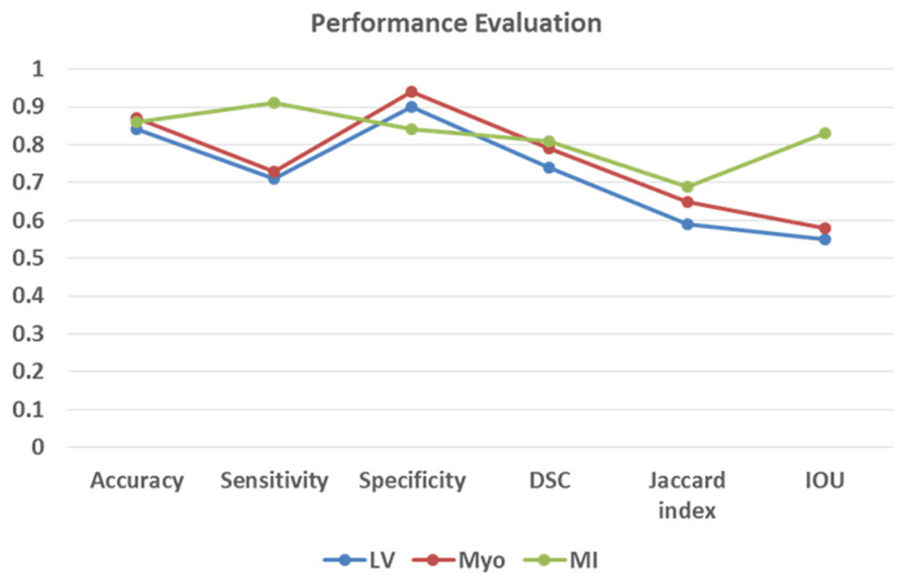

Fig. 4. Evaluation metrics of proposed network's performance

The visualization results of the proposed network are depicted in Figure 5, which shows a good detection of MI area in cardiac LGE-MRI images. Despite the complex shape of the scar and the edema in MRI images, the segmentation outcomes look reasonable, and the infarcted area is consistent with the MI area in the ground truth. A confusion matrix is a summary of computed results from the predicted pixel labels and ground truth pixel labels. The confusion matrix is shown in Figure 6 for model performance evaluation. The percentage of detected pixels for LV, Myo and MI, are 70.94%, 73.49% and 90.68%, respectively.

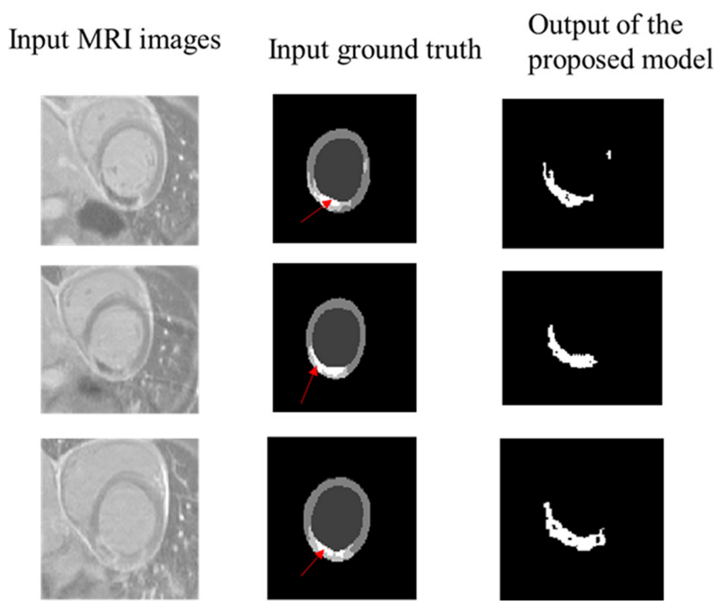

Fig. 5. The results of detected MI region by CNN network

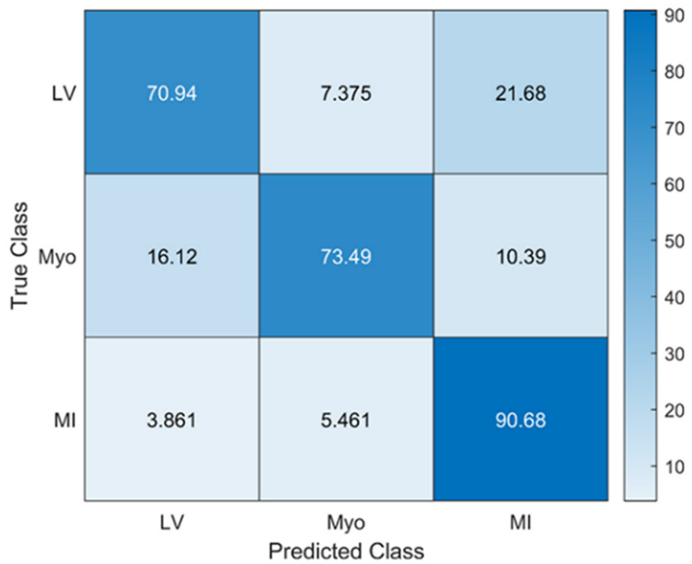

Fig. 6. The confusion matrix of the proposed CNN segmentation network

To validate and assess the results of the proposed model, quantitative comparison with three previous methods were applied. Table 2 presents the quantitative comparison results which are based on three evaluation metrics consists of accuracy, DSC and IOU. As shown in the table, it is obvious that the proposed model outperforms other methods in term of MI area segmentation by achieving 0.86, 0.83 and 0.81 for accuracy, IOU and DSC, respectively. The accuracy and DSC of the model proposed in [38] are higher due to applying various models with multi-level and multi scale variation encoders for features learning. Although this proposed network has achieved the desired performance in MI detection, it lacks the detection of MI area in some apical slices. Moreover, the results need to be checked by a clinician to confirm the performance of the proposed CNN segmentation model.

Table 2. Performance comparison between the proposed model and other state-of-the-art models in MI segmentation (MICCAI = Medical Image Computing and Computer Assisted Interventions)

Method	Dataset	Metrics		
		Accuracy	IOU	DSC
Proposed network	EMIDEC	0.86	0.83	0.81
Popescu *et al*. [39]	MICCAI 2015	0.86	0.68	0.75
Bleton *et al*. [40]	MICCAI 2015	0.84	0.64	0.72
Xu *et al*. [38]	MICCAI 2018	0.96	0.79	0.90

5 Conclusions

This paper proposed a fully automatic CNN network to segment myocardial infarction with irregular and complex shapes from LGE-MRI images. Experimental results have shown the network's effectiveness in segmenting the anatomical structures of the infarcted area. The model achieved values of 0.86, 0.91, 0.84, 0.81, 0.69 and 0.83 for accuracy, sensitivity, specificity, dice score coefficient (DSC), Jaccard index and intersection over union (IOU), respectively. Visually, the automatic scar segmentation is consistent with manually labelled ground truth by experts. Integrating hybrid model using classification model to extract clinical features and segmentation model for feature extraction from LGE-MRI to detect myocardial infarction is suggested for future work.

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7 References

[1] E. J. Benjamin *et al.*, "Heart disease and stroke statistics—2019 Update: A report from the American heart association," *Circulation*, vol. 139, no. 10, Mar. 2019, https://doi.org/10.1161/CIR.0000000000000659

[2] R. L. McNamara *et al.*, "Predicting in-hospital mortality in patients with acute myocardial infarction," *J. Am. Coll. Cardiol.*, vol. 68, no. 6, pp. 626–635, Aug. 2016, https://doi.org/10.1016/j.jacc.2016.05.049

[3] M. Kumar, R. B. Pachori, and U. R. Acharya, "Automated diagnosis of myocardial infarction ECG signals using sample entropy in flexible analytic wavelet transform framework," *Entropy*, vol. 19, no. 9, p. 488, Sep. 2017, https://doi.org/10.3390/e19090488

[4] U. B. Baloglu, M. Talo, O. Yildirim, R. S. Tan, and U. R. Acharya, "Classification of myocardial infarction with multi-lead ECG signals and deep CNN," *Pattern Recognit. Lett.*, vol. 122, pp. 23–30, May 2019, https://doi.org/10.1016/j.patrec.2019.02.016

[5] U. R. Acharya *et al.*, "Automated detection and localization of myocardial infarction using electrocardiogram: A comparative study of different leads," *Knowledge-Based Syst.*, vol. 99, pp. 146–156, May 2016, https://doi.org/10.1016/j.knosys.2016.01.040

[6] J. Cheng, S. Tian, L. Yu, X. Ma, and Y. Xing, "A deep learning algorithm using contrast-enhanced computed tomography (CT) images for segmentation and rapid automatic detection of aortic dissection," *Biomed. Signal Process. Control*, vol. 62, p. 102145, Sep. 2020, https://doi.org/10.1016/j.bspc.2020.102145

[7] Y. Guo *et al.*, "Automatic left ventricular cavity segmentation via deep spatial sequential network in 4D computed tomography," *Comput. Med. Imaging Graph.*, vol. 91, p. 101952, Jul. 2021, https://doi.org/10.1016/j.compmedimag.2021.101952

[8] Z. Chen *et al.*, "Automatic deep learning-based myocardial infarction segmentation from delayed enhancement MRI," *Comput. Med. Imaging Graph.*, vol. 95, p. 102014, Jan. 2022, https://doi.org/10.1016/j.compmedimag.2021.102014

[9] K.-N. Wang *et al.*, "AWSnet: An auto-weighted supervision attention network for myocardial scar and edema segmentation in multi-sequence cardiac magnetic resonance images," *Med. Image Anal.*, vol. 77, p. 102362, Apr. 2022, https://doi.org/10.1016/j.media.2022.102362

[10] Z. Chen *et al.*, "Automatic deep learning-based myocardial infarction segmentation from delayed enhancement MRI," *Comput. Med. Imaging Graph.*, vol. 95, p. 102014, Jan. 2022, https://doi.org/10.1016/j.compmedimag.2021.102014

[11] K. Brahim, A. Qayyum, A. Lalande, A. Boucher, A. Sakly, and F. Meriaudeau, "A 3D network based shape prior for automatic myocardial disease segmentation in delayed-enhancement MRI," *IRBM*, vol. 42, no. 6, pp. 424–434, Dec. 2021, https://doi.org/10.1016/j.irbm.2021.02.005

[12] Z. F. Shaaf, M. M. A. Jamil, and R. Ambar, "Automatic localization of the left ventricle from short-axis MR images using circular hough transform," in *Lecture Notes in Networks and Systems*, vol. 348, pp. 501–508, 2022, https://doi.org/10.1007/978-981-16-7597-3_41

[13] C.-Q. Huang, J.-K. Chen, Y. Pan, H.-J. Lai, J. Yin, and Q.-H. Huang, "Clothing landmark detection using deep networks with prior of key point associations," *IEEE Trans. Cybern.*, vol. 49, no. 10, pp. 3744–3754, Oct. 2019, https://doi.org/10.1109/TCYB.2018.2850745

[14] J. Liu *et al.*, "Myocardium segmentation from DE MRI using multicomponent gaussian mixture model and coupled level set," *IEEE Trans. Biomed. Eng.*, vol. 64, no. 11, pp. 2650–2661, Nov. 2017, https://doi.org/10.1109/TBME.2017.2657656

[15] J. Liu *et al.*, "Myocardium segmentation combining T2 and DE MRI using multi-component bivariate gaussian mixture model," in *2014 IEEE 11th International Symposium on Biomedical Imaging (ISBI)*, pp. 886–889, 2014, https://doi.org/10.1109/ISBI.2014.6868013

[16] A. O. Al-Agamy, N. F. Osman, and A. S. Fahmy, "Myocardium segmentation in strain-encoded (SENC) magnetic resonance images using graph-cuts," *IET Image Process.*, vol. 7, no. 5, pp. 415–422, Jul. 2013, https://doi.org/10.1049/iet-ipr.2012.0513
[17] Wenjia Bai *et al.*, "A probabilistic patch-based label fusion model for multi-atlas segmentation with registration refinement: Application to cardiac MR images," *IEEE Trans. Med. Imaging*, vol. 32, no. 7, pp. 1302–1315, Jul. 2013, https://doi.org/10.1109/TMI.2013.2256922
[18] C. Yang, W. Wu, Y. Su, and S. Zhang, "Left ventricle segmentation via two-layer level sets with circular shape constraint," *Magn. Reson. Imaging*, vol. 38, pp. 202–213, May 2017, https://doi.org/10.1016/j.mri.2017.01.011
[19] O. M. Al-hazaimeh, A. Abu-Ein, N. Tahat, M. Al-Smadi, and M. Al-Nawashi, "Combining artificial intelligence and image processing for diagnosing diabetic retinopathy in retinal fundus images," *Int. J. Online Biomed. Eng.*, vol. 18, no. 13, pp. 131–151, Oct. 2022, https://doi.org/10.3991/ijoe.v18i13.33985
[20] H. Vega-Huerta *et al.*, "Convolutional neural networks on assembling classification models to detect melanoma skin cancer," *Int. J. Online Biomed. Eng.*, vol. 18, no. 14, pp. 59–76, Nov. 2022, https://doi.org/10.3991/ijoe.v18i14.34435
[21] H. Ayad, I. W. Ghindawi, and M. S. Kadhm, "Lung segmentation using proposed deep learning architecture," *Int. J. online Biomed. Eng.*, vol. 16, no. 15, pp. 141–147, Dec. 2020, https://doi.org/10.3991/ijoe.v16i15.17115
[22] Z. F. Shaaf, M. M. A. Jamil, R. Ambar, A. A. Alattab, A. A. Yahya, and Y. Asiri, "Automatic left ventricle segmentation from short-axis cardiac MRI images based on fully convolutional neural network," *Diagnostics*, vol. 12, no. 2, p. 414, Feb. 2022, https://doi.org/10.3390/diagnostics12020414
[23] X. Du *et al.*, "An integrated deep learning framework for joint segmentation of blood pool and myocardium," *Med. Image Anal.*, vol. 62, pp. 1–17, 2020, https://doi.org/10.1016/j.media.2020.101685
[24] L. Qi *et al.*, "Multi-scale feature fusion convolutional neural network for concurrent segmentation of left ventricle and myocardium in cardiac MR images," *J. Med. Imaging Heal. Informatics*, vol. 10, no. 5, pp. 1023–1032, May 2020, https://doi.org/10.1166/jmihi.2020.3005
[25] X. Du, S. Yin, R. Tang, Y. Zhang, and S. Li, "Cardiac-DeepIED: Automatic pixel-level deep segmentation for cardiac bi-ventricle using improved end-to-end encoder-decoder network," *IEEE J. Transl. Eng. Heal. Med.*, vol. 7, Art no. 1900110, pp. 1–10, 2019, https://doi.org/10.1109/JTEHM.2019.2900628
[26] Z. F. Shaaf, M. M. A. Jamil, and R. Ambar, "A review on left ventricle segmentation and quantification by cardiac magnetic resonance images using convolutional neural networks," *Maejo International Journal of Science and Technology*, vol. 15, no. 3. pp. 273–292, 2021.
[27] L. K. Tan, Y. M. Liew, E. Lim, and R. A. McLaughlin, "Convolutional neural network regression for short-axis left ventricle segmentation in cardiac cine MR sequences," *Med. Image Anal.*, vol. 39, pp. 78–86, Jul. 2017, https://doi.org/10.1016/j.media.2017.04.002
[28] X. Yang, Z. Zeng, and S. Yi, "Deep convolutional neural networks for automatic segmentation of left ventricle cavity from cardiac magnetic resonance images," *IET Comput. Vis.*, vol. 11, no. 8, pp. 643–649, Dec. 2017, https://doi.org/10.1049/iet-cvi.2016.0482
[29] L. Xie, Y. Song, and Q. Chen, "Automatic left ventricle segmentation in short-axis MRI using deep convolutional neural networks and central-line guided level set approach," *Comput. Biol. Med.*, vol. 122, p. 103877, Jul. 2020, https://doi.org/10.1016/j.compbiomed.2020.103877
[30] S. Moradi *et al.*, "MFP-Unet: A novel deep learning based approach for left ventricle segmentation in echocardiography," *Phys. Medica*, vol. 67, pp. 58–69, Nov. 2019, https://doi.org/10.1016/j.ejmp.2019.10.001

[31] Y. Chang and C. Jung, "Automatic cardiac MRI segmentation and permutation-invariant pathology classification using deep neural networks and point clouds," *Neurocomputing*, vol. 418, pp. 270–279, Dec. 2020, https://doi.org/10.1016/j.neucom.2020.08.030
[32] X. Sun, P. Garg, S. Plein, and R. J. Geest, "SAUN: Stack attention U-Net for left ventricle segmentation from cardiac cine magnetic resonance imaging," *Med. Phys.*, vol. 48, no. 4, pp. 1750–1763, Apr. 2021, https://doi.org/10.1002/mp.14752
[33] H. B. Winther *et al.*, "ν-net," *JACC Cardiovasc. Imaging*, vol. 11, no. 7, pp. 1036–1038, Jul. 2018, https://doi.org/10.1016/j.jcmg.2017.11.013
[34] O. Bernard *et al.*, "Deep learning techniques for automatic MRI cardiac multi-structures segmentation and diagnosis: Is the problem solved?," *IEEE Trans. Med. Imaging*, vol. 37, no. 11, pp. 2514–2525, Nov. 2018, https://doi.org/10.1109/TMI.2018.2837502
[35] M. Pérez-Pelegrí *et al.*, "Automatic left ventricle volume calculation with explainability through a deep learning weak-supervision methodology," *Comput. Methods Programs Biomed.*, vol. 208, p. 106275, Sep. 2021, https://doi.org/10.1016/j.cmpb.2021.106275
[36] M. Mamalakis, P. Garg, T. Nelson, J. Lee, J. M. Wild, and R. H. Clayton, "MA-SOCRATIS: An automatic pipeline for robust segmentation of the left ventricle and scar," *Comput. Med. Imaging Graph.*, vol. 93, p. 101982, Oct. 2021, https://doi.org/10.1016/j.compmedimag.2021.101982
[37] A. Lalande *et al.*, "Emidec: A database usable for the automatic evaluation of myocardial infarction from delayed-enhancement cardiac MRI," *Data*, vol. 5, no. 4, p. 89, Sep. 2020, https://doi.org/10.3390/data5040089
[38] C. Xu, J. Howey, P. Ohorodnyk, M. Roth, H. Zhang, and S. Li, "Segmentation and quantification of infarction without contrast agents via spatiotemporal generative adversarial learning," *Med. Image Anal.*, vol. 59, p. 101568, Jan. 2020, https://doi.org/10.1016/j.media.2019.101568
[39] I. A. Popescu, B. Irving, A. Borlotti, E. Dall'Armellina, and V. Grau, "Myocardial scar quantification using SLIC supervoxels – parcellation based on tissue characteristic strains," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, pp. 182–190, 2017, https://doi.org/10.1007/978-3-319-52718-5_20
[40] H. Bleton, J. Margeta, H. Lombaert, H. Delingette, and N. Ayache, "Myocardial infarct localization using neighbourhood approximation forests," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, pp. 108–116, 2016, https://doi.org/10.1007/978-3-319-28712-6_12

8 Authors

Zakarya Farea Shaaf received his B.Sc. (Hons) in Electronic Engineering from Universiti Tun Hussein Onn Malaysia (UTHM) in 2016. He then enrolled at Universiti Tun Hussein Onn Malaysia, in 2016, where he was awarded the M.Sc. in Electrical Engineering in 2018. Currently, he is a Ph.D. candidate in the department of electrical engineering, UTHM. He 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. His research interests in deep learning models, image processing, cardiac MRI and cardiovascular disease detection. (Email: zakaryashaaf@gmail.com).

Muhammad Mahadi Abdul Jamil started his further education with a higher national diploma in medical electronic engineering at the British Malaysian Institute. He then moved on to the University of Bradford where he gained Bachelor Degree with Honours in Medical Engineering in year 2003. Later completed his higher education in 2007. This is when Dr Mahadi gained his Phd degree in Medical Engineering from the same university. Dr Mahadi's career shortly began in 2008. He shared his extensive knowledge by lecturing in UTHM, Batu Pahat, Johor. He has gained a vast range of specializations since then. From then on he has also joined and participated in a variety of professional societies, currently being the Board of Engineers Malaysia and the International Association of Engineers. One of his many accomplishments consist of the various publications he has produced during the 14 years of his career. Not to forget the many research grants and contracts he has acquired over the years. Alongside this, he has kept himself busy by supervising numerous students on their Bachelor Degree, Master and PhD projects. His research interest and focus are in the field of biomedical engineering system and applications technology. (Email: mahadi@uthm.edu.my).

Radzi Ambar is a senior lecturer of Computer Engineering Field at the Faculty of Electrical and Electronic Engineering (FKEE), Universiti Tun Hussein Onn Malaysia (UTHM). He received a Diploma in Control and Information Systems Engineering from Tsuruoka National College of Technology, Japan. Then, he received his B.Eng. degree in Information and Computer Science Engineering from Toyohashi University of Technology, Japan. He obtained his MSc. degree in Electrical Engineering in 2011 from Universiti Tun Hussein Onn Malaysia. Then, he received his Dr. Eng. in Mechanical and Control Engineering (Robotics) from Kyushu Institute of Technology, Japan in 2015. Previously, he worked as a R&D software engineer for Panasonic Communication (Malaysia) Sdn. Bhd. and SHARP Manufacturing (Malaysia) Sdn. Bhd. as a quality assurance engineer for 2 years. His research interests include mechatronics, underwater and mobile surface robotics, assistive devices for rehabilitation and agriculture robotics. He has authored and co-authored in various international book chapters as well as published more than 100 technical papers in conferences and peer-reviewed journals. (Email: aradzi@uthm.edu.my).

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