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Left Ventricle Segmentation using Bidirectional Convolution Dense Unet

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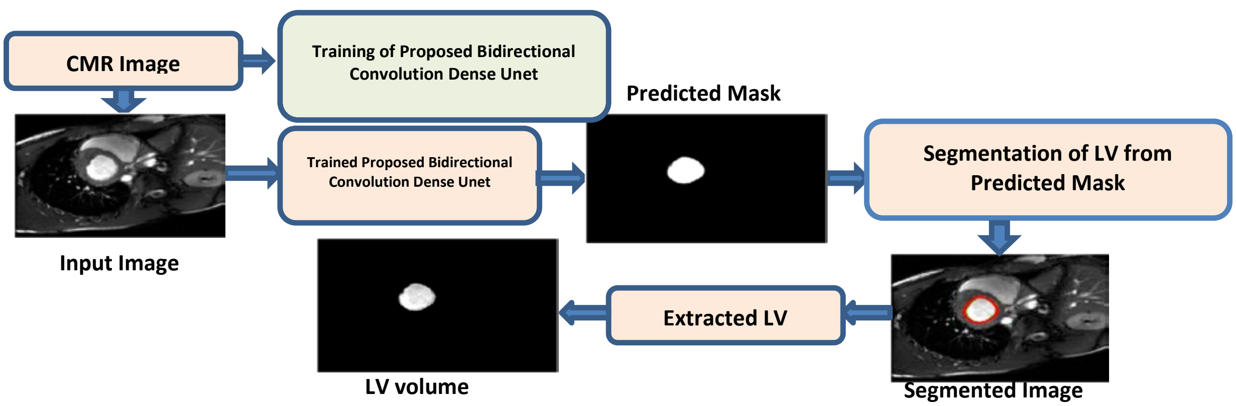
ABSTRACT



Cardiac magnetic resonance technique is a most useful technique to diagnose early cardiovascular diseases as a noninvasive method to reduce the mortality rate. There are so many methods developed to locate the heart chambers to derive cardiac indices, among them left ventricle plays an important role. Due to the overlapping of the heart chamber during a different cardiac phase, the segmentation of the left ventricle (LV) is a challenging task. To improve segmentation of the Left ventricle, we propose a dense Unet-based architecture with bidirectional convolution LSTM (long short-term Memory). In this method, dense block and bidirectional convolution are used to extract diverse features from Cardiac Magnetic Resonance (CMR) image to locate the LV cavity. We use the publicly available Automated Cardiac Diagnosis Challenge (ACDC) dataset for training and testing of the proposed model. The proposed method achieved high dice score of 0.97(ED) & 0.92(ES) for the ACDC test dataset. The proposed model was also tested on Multi-Vendor and Multi-Disease Cardiac Image Segmentation Challenge (M & M) dataset and achieves a 0.897 dice score that demonstrates the effectiveness and robustness of the network.

Keywords: Medical Imaging, Deep learning, CMR image Analysis, Left Ventricle segmentation, Semantic Segmentation, MRI

INTRODUCTION

Cardiovascular diseases are responsible for the highest mortality rate worldwide. CMR technique provides a non-invasive method to diagnose CVDs by deriving cardiac indices such as End diastole volume (EDV) and End systole volume (ESV), which is a measure of the amount of blood that is pumped in one cardiac cycle. Currently, Cardiologist manually analyzes the CMR images which are time consuming and labor-intensive methods also that is prone to high inter and intra observer variability.[1] There are always some discrepancies between the different human labelers to segment manually Heart structure and quantitative assessment.[2] So, there is no easy way available to segment the LV chamber accurately which is the largest chamber in the heart and plays a critical role in cardiac functions. LV segmentation task refers to detecting LV contour or endocardial surface. LV segmentation from CMR images is a challenging task due to poor contrast of heart tissue, overlapping chambers of the heart, continuous movement of heart during diastole and systole phase, variable wall thickness and small blood pool available in apical slices, and overlapping of chambers in basal

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heart slices in MR images. For experts also it can take an hour to segment LV manually for a single patient.[3,4] Earlier, CMR segmentation has been carried out by discontinue-based, region based segmentation and atlas based segmentation methods which require prior information of pixel values. The previous state of the art has limited scope because of variability in cardiac anatomic and functions for a different group of subjects and Multi MRI Scanners.[5] Whereas, deep learning based segmentation is automatic finds the key features from data, and localizes objects by using supervised learning. This makes semantic segmentation easy to apply for various diagnosis applications in medical image analysis.[6,7]

This paper provides a proposed method to segment left ventricles accurately by using Unet based architecture with dense block and bidirectional convolution long short term Memory (LSTM) which has filters to learn features automatically, there is no requirement of benchmarks or prior landmark information. This paper organized as, section 2 briefly describes previous LV segmentation methods based on deep learning. Section 3 describes the methodology of the proposed method to segment the Left ventricle by using bidirectional convolutional Dense Unet. Section 4 reports results and analysis of the proposed method on the Automated Cardiac Diagnosis Challenge (ACDC) dataset and Multi center, Multi-Vendor, and Multi-Disease Cardiac Image Segmentation Challenge (M & M) challenge dataset. Finally, Section 5 concludes the summary of the performance of the proposed method on the CMR dataset.

PREVIOUS WORK

The task of localization of LV endocardium and epicardium from cine MRI for systole and diastole phase of the cardiac cycle has received much research focus and attention over the past decade. Adam Budai et. al.[8] found LV contour by using Region of interest (ROI) estimation and control point regression in place of dense segmentation. They used Resnet to detect 40 Control points by using a pseudo gradient. Yan Xia et.al.[9] developed Generative Adversarial (GAN) network to find the missing slices or information from CMR to calculate accurate LV volume. Adan Lin et.al.[10] developed a shape model for data augmentation to prevent Overfitting for small datasets. They trained data using a fully convolution network (FCN) and found that, balance datasets with diverse features improve the performance of the network. Hisham Abdeltawab et. al.[11] developed two networks, FCN1 for ROI detection and FCN 2 to localize the LV cavity. Authors trained their networks by introducing a new radial loss functions that minimizes the distance between predicted and true contour. Youssef Skandarani et. al.[12] analyzed three networks: Unet and its variants with different loss function on M& M dataset and ACDC dataset and found good performance for non expert ground truth over expert ground truth used to train network. Luo C et. al.[13] proposed unet with the combination of image slice sequences. In this method, existing prediction depended on the previous slice label. G. Simantiris et.al.[14] developed dilated CNN to localize LV, RV, and MYO which maintain full resolution for each layer of the network. This approach reduced trained parameters but is not applicable to fetch volume information. M. Chen et.al.[15] developed a focal residual block to restore the features that were lost in down sampling path by calculating focal loss. Shaaf ZF et. al.[16] trained the FCN network using different hyperparameters of network and data normalization to improve the performance.

Wang Z et. al.[17] designed FCN with adjustable pixel weight based on the segmentation accuracy of the upper layer. This approach improved the performance of network for apical and basal slices. C. V. Graves et. al.[18] used histogram matching and CLAHE for pre-processing and Unet to localize the LV cavity by aggregating two different datasets to improve the robustness of network. Bofeng Wu et. al.[19] combined FCN to extract ROI from down-sampled images and Unet to find LV cavity. This approach failed for LV boundary fitting and detection of LV cavity compared to cardiologist do. Wang Y et. al.[20] used multi-channel FCN to extract ROI and the level set method to find accurate LV boundaries. Marco Penso et al.[21] used Unet model with dense block to concatenate its own feature maps with the feature map of all preceding layers to add and preserve information. This approach had found difficulties to localize RV and basal slices. Zabihollahy F. et. al.[22] developed cascade Unet to find out LV boundaries and scar from 3D LGE MR Images. This approach had found difficulties to segment apical and basal slices. Zarvani M et. al.[23] developed residual Unet by adding three level wise shortcut connections to prevent vanishing and exploding gradient problems, which provide information exchange between branches.

METHODOLOGY

Segmentation of the left ventricle (LV) from MR images is an essential step for the calculation of clinical indices such as ventricular volume and ejection fraction. We proposed Unet based architecture with bidirectional convolution and dense block to segment LV contour. The framework of the proposed approach is given in figure 1. This modified Unet architecture used both bidirectional convolution and dense block for LV segmentation.

DATASET

We use the Automated Cardiac Diagnosis Challenge (ACDC) or MICCAI challenge 2017 dataset[24] and Multi center, Multi-Vendor and Multi-Disease Cardiac Image Segmentation Challenge (M &Ms) dataset (MICCAI 2020).[25] ACDC dataset is composed of 150 subject images by dividing into 100 for train set and 50 for test set. This dataset was divided into 5 subgroups: 4 pathological (myocardial infarction, dilated cardiomyopathy, hypertrophic cardiomyopathy, abnormal right ventricle) and 1 healthy subject group. It contains ground truth for LV, RV, and MYO along with diastolic and systolic phase instants. We divided the dataset into a train set to train the model and a test set to evaluate the model. The Train set contains total of 85 subject images among them, 17 images for normal cases and 17 for each pathological case. Test set contains total 15 subject's images among them, 3 for normal case and 3 for each pathological case.

M&Ms is composed of 375 subject's images with hypertrophic and dilated cardiomyopathy as well as healthy subjects. This dataset's images are captured by using four different MRI scanners at different countries centers Spain, Germany, and Canada. The training set contains 150 annotated images and 25 unannotated with groundtruth for LV, RV, and MYO. The test set contains 200 subjects' images.

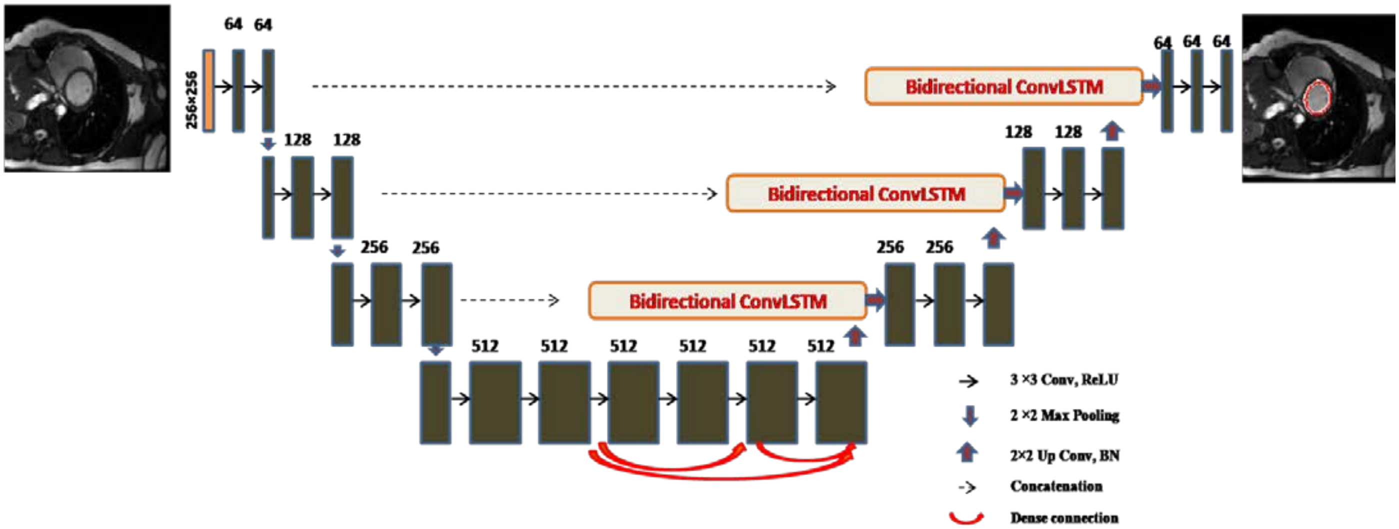

Figure 1. The Architecture of Proposed Network.

Data Augmentation

Overfitting problems are occurred in the deep network for medical image segmentation due to less number of images. To solve this problem, data augmentation is carried out for small datasets which is helpful to reduce the Overfitting problem and generalize the network by enhancing its performance. Data augmentation is creating variations in the existing image to expand the datasets. It is carried out by using image processing techniques like rotation, scaling, and shearing, zooming. In this proposed approach, the rotation of the image is done by 0.3, 0.4, ,and 0.5 degrees with the Shearing of image by 0.07 degrees in x-axis, and scaling of the image is done by zooming out scaling factor 0.07 × original size.

Architecture of Proposed Network

In this proposed approach, we input the original image to the network for training that has a size of 256 × 256. This proposed architecture has three parts: contracting, bottleneck, and expanding path as shown in figure 1. The Contracting path has four blocks. Each block consists of two convolutional 3*3 filters followed by 2*2 max pooling and ReLU functions. The number of feature maps is doubled at each block and the size of the feature maps becomes half. The contracting path extracts high resolution features. The output of the last block of contracting path is passed to the bottleneck through two 3 ×3 convolution layers. This network has a dense block at bottleneck in which the network reuses the feature map and improves the performance of network. In dense block, feature map learns at the first block of bottleneck is forwarded to the next each of two blocks in bottleneck followed by two consecutive convolutions. If consider f_e^i as the ith output of convolution block, the input of ith convolutional block receives the concatenation of the feature maps of all preceding convolutional blocks as its input. That means feature map as input $[f_e^1, f_e^2, f_e^3, \ldots, f_e^N] \in R^{(i-1)F_l \times W_l \times H_l}$, and the output of ith block is $f_e^i \in R^{(i)F_l \times W_l \times H_l}$.[26] This technique reduces redundant information and helps to learn diverse features for enhancement of information flow based on gained knowledge at previous layers.

The expanding path has also four blocks. Each block performs upsampling on the previous layer output feature map and gives more semantic information. The corresponding contracting path feature map is copied and concatenated with the output of expanding path by using bidirectional convolution LSTM which gives a more precise segmentation output than the simple concatenation of Unet. If feature map, $f_e^i \in R^{(i)F_l \times W_l \times H_l}$, is copied from the contracting path and previous convolutional layer feature map is $f_d^i \in R^{(i)F_{l+1} \times W_{l+1} \times H_{l+1}}$, then, $f_{l+1}=2 \times f_l$, $W_{l+1} = 0.5 \times W_l$ and $H_{l+1}=0.5 \times H_l$. In the decoding path, upsampling followed by 3 × 3 convolution are applied, that double the size of each feature map and half the number of feature channels, $f_d^i \in R^{(i)F_l \times W_l \times H_l}$ as a result that reaches original image size layer by layer.[26] The upsampling function is followed by batch normalization to increase network stability by standardizing the inputs to a layer by subtracting of batch mean and dividing batch standard deviation. The output of batch normalize is fed to bidirectional convolutional LSTM to do convolution into input-to-state and state-to-state transitions. This block consists of controlling gates like input gate i_t to access, an output gate o_t to update, a forget gate ft to clear memory, and a memory cell Ct like LSTM net. This block processes the data in two directions forward and backward path and then makes a decision for the current input by dealing with the data dependencies in both directions to improve the predictive performance of the network.

Finally, the sigmoid function is used to obtain predict segmentation which is predicted probability as output between 0 and 1,

$$f(x) = \frac{1}{1+e^{-x}} \qquad (1)$$

The cost function l_{ce} is calculated as a binary cross entropy function as follows:

$$l_{ce} = \sum_{i=1}^{n} y_i . log\hat{y_i} + (1-y_i).\log(1-\hat{y_i}) \quad (2)$$

Where $\hat{y}_i$ is the ith scalar value in the model output and y_i is the target value. Then we utilize the Adam optimizer to reduce cost function.

Training and Evaluation of Network

ACDC dataset provides CMR images for End diastole (ED) and End systole (ES) phase instants of the cardiac cycle. The proposed network is trained in three different ways by using ED and ES phase CMR images separately and then combining of two phases. There is the total of 1072 short axis view CMR images extracted from the End diastole phase volume of ACDC dataset and 984 CMR images from End systole phase volume of ACDC dataset. The CMR images for both the ED and ES phases are 2024 images with the corresponding groundtruth for LV region. The train dataset contains 936 short axis view slices for ED phase, in which 4 pathological subjects and normal subjects' images are included. The test dataset contains 136 short axis view slices for the validation of ED phase accuracy of trained network. The train dataset for ES phase contains 880 short axis views, in which 4 pathological subjects and normal subjects' images are included. The test dataset contains 104 short axis view slices for the validation of ES phase accuracy of the trained network.

The proposed network is trained by using an initial learning rate $1e^{-4}$ and then it is reduced by decay factor 0.1 with 150 epochs. Adam optimizer with β_1 0.9 and β_2 0.999 is used to optimize the proposed model as an efficient optimizer when working with large trainable parameters. To prevent Overfitting problem during training, batch size 8 is added for batch normalization after each convolution layer which regularizes weights and reduces generalizing error.

The experiments is done by using Tensorflow 2.0 and python 2.7 at the super computer platform Param savak which has processor Dual Socket Intel Xeon E5-2680 v4 with 14 cores each with 2.4 GHz clock speed, 64 GB RAM , 8 TB HDD, 16 GB GPU memory.

The evaluation of proposed model is done by using Dice coefficient (Dice) and Jaccard distance (JD). That is calculated as,

$$JD = \frac{|gt_i \times p_i|}{|gt_i| + |p_i| - |gt_i \times p_i|} \quad (3)$$

$$L_{dice} = \frac{2 \times \sum |gt_i \times p_i|}{\sum |gt_i| + \sum |p_i|} \quad (4)$$

Where, g_{ti} is true value of groundtruth, p_i is the predicted value for segmentation. Dice score defines the overlapping region between the groundtruth and predicted image, as the 1 value is best segmentation result. Jaccard distance defines the number of count shared by ground truth and predicted mask.

Experimental Results and Discussion

In this section, we present the training and testing results of our proposed network on ACDC dataset and Multi center, Multi-Vendor and Multi-Disease Cardiac Image Segmentation Challenge (M &Ms) dataset. At the end of this section, we compare our model with current methods of LV segmentation. There is a predicted binary mask is obtained from proposed model for LV segmentation. This predicted mask is surrounded on LV region in original image with red line and groundtruth with green line to show how accurately fits the contours. ACDC dataset contains a variety of images like different disease group subjects, contrast of images due to inhomogeneity of the heart tissues, and varying acquisition conditions for CMR scanners. We have selected one CMR image for each disease case randomly from the test dataset for End diastole and End systole phase instant and show results of segmentation in figure 2 and figure 3.

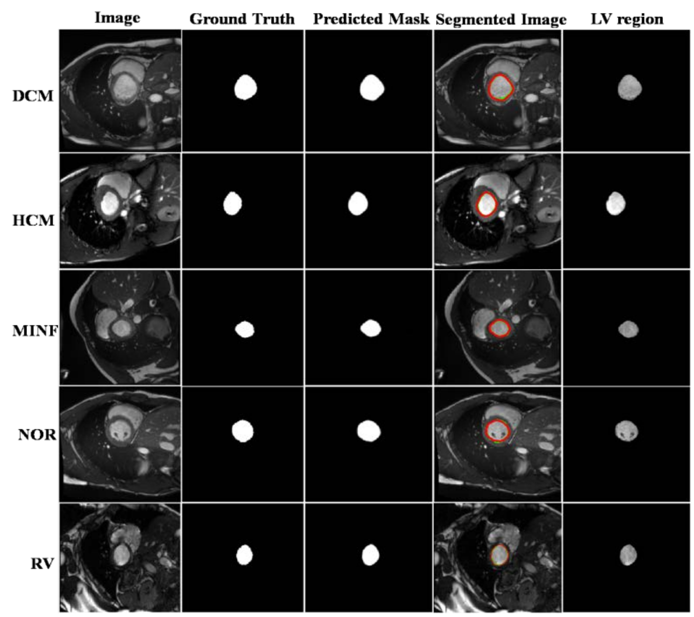

Figure 2. Segmentation results of proposed network for End Diastole phase Test dataset. The Red colour contour shows predicted mask by network and Green colour contour shows True binary mask.

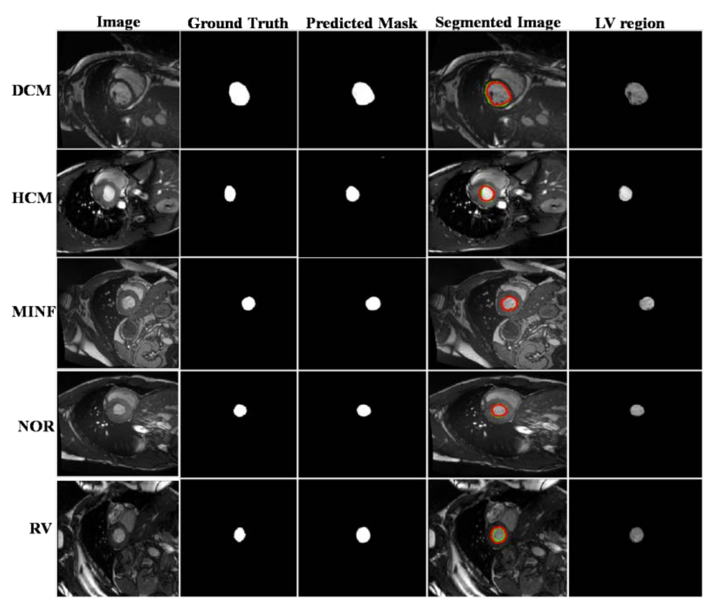

Figure 3 Segmentation results of proposed network for End Systole phase Test dataset. Red colour contour shows predicted mask by network and Green colour contour shows True binary mask.

The proposed model accurately works on mid phase slices for all the disease case CMR images. Our model gives remarkable results as dice score and Jaccard distance for different cardiac phases as shown in table 1.

Table 1: Results of proposed Network for LV segmentation.

Model	Dataset	ED		ES		ED & ES	
		Dice	JD	Dice	JD	Dice	JD
Proposed	Training	0.99	0.98	0.94	0.93	0.97	0.96
	Testing	0.96	0.95	0.92	0.91	0.92	0.91

We have observed that the proposed network achieves high dice score of 0.967 for ED phase instant than dice score of 0.92 for ES phase instant of test dataset because during ED phase LV volume is highly visible due to high blood pool in LV cavity compared to ES phase. This proposed model achieves high dice score of 0.976 for the training dataset of both phase instant (ED & ES) and 0.93 for the testing dataset of both phase instant (ED & ES) as shown in table 1. These results prove the robustness and effectiveness of the proposed model.

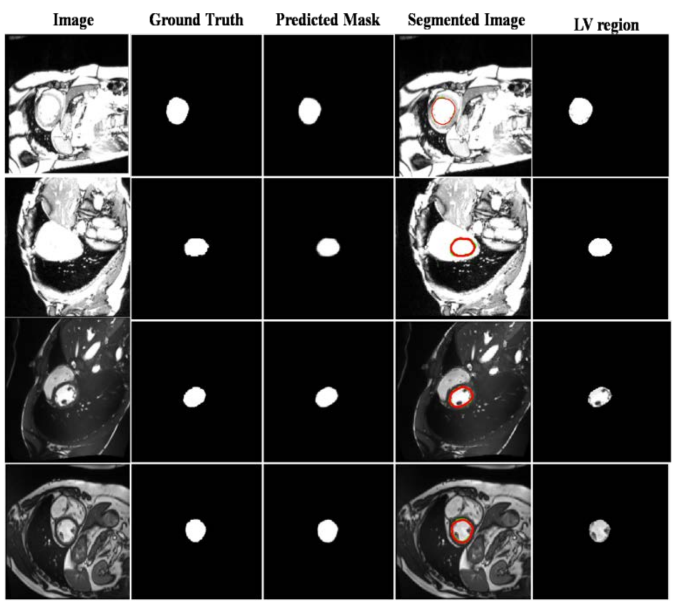

Figure 4. Segmentation results of proposed network for challenges cases which have poor contrast or papillary muscles in LV cavity. Red colour contour shows predicted mask by network and Green colour contour shows True binary mask.

In CMR segmentation, there are so many challenges to segment the heart structures accurately. Because of the continuous movement of heart wall, CMR images have poor contrast and also the overlapping of LV and RV regions. There is one more challenge to locate LV region accurately in the presence of papillary muscles in LV cavity. Our proposed model works accurately on short axis CMR slices which have poor contrast and papillary muscles are present in LV cavity as shown in figure 4. The first two cases have poor contrast between heart structures although the model can segment LV cavity accurately. In this type of cases, the experts locate region manually by using their experience. Our model works

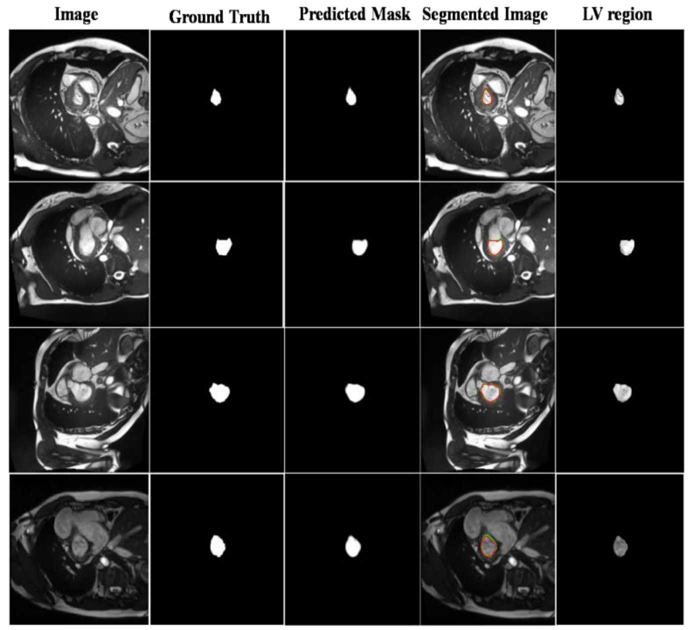

Figure 5. Segmentation results of proposed network for Basal slices. Red colour contour shows predicted mask by network and Green colour contour shows True binary mask.

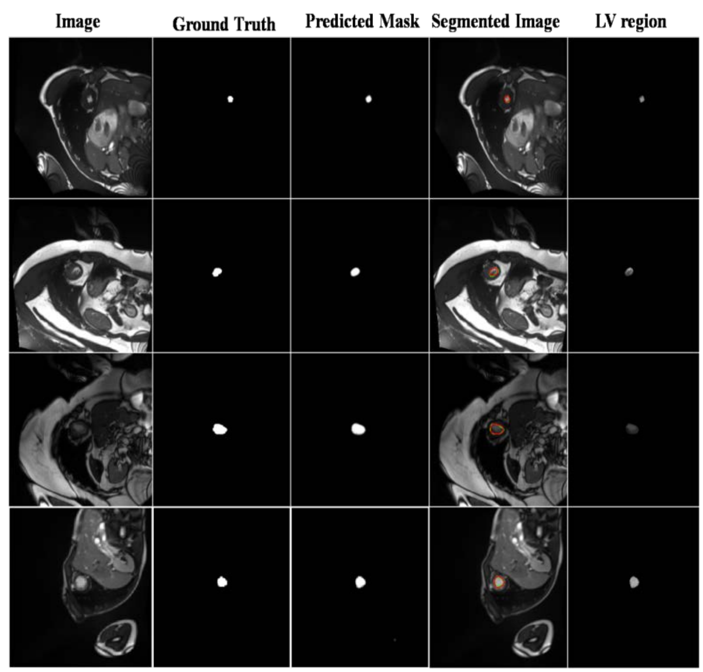

Figure 6. Segmentation results of proposed network for apical slices. Red colour contour shows predicted mask by network and Green colour contour shows True binary mask.

well for last two cases which have papillary muscles in LV cavity.

The LV region of mid phase slices of CMR can be accurately localized. But, there are difficulties to locate LV region for basal slices and apical slices. In basal slices, heart chambers are overlapped on each other so, the complete LV region is not visible. The proposed network gives remarkable results for basal slice segmentation as shown in figure 5. In apical slices, blood volume is low in LV region. So, that it is difficult to delineate the boundary of LV region. As shown in figure 6, proposed model segments the LV region accurately in apical slices.

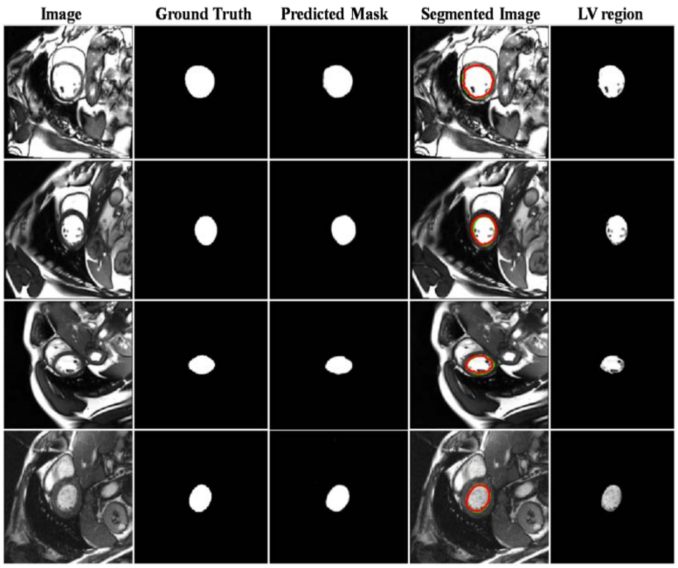

Figure 7. Segmentation results of proposed network for M and M dataset. Red colour contour shows predicted mask by network and Green colour contour shows True binary mask.

The proposed network was tested on Multi-Vendor and Multi-Disease Cardiac Image Segmentation Challenge (M &Ms) dataset (MICCAI 2020) and shows segmentation results in figure 7. The proposed model achieves a test dice score of 0.897 for total of 676 CMR image slices of M & M dataset. The current methods work very well for one trained dataset. But, our model gives remarkable LV segmentation results on another dataset as well. Hence it proves its robustness for varieties of image that are acquired in different conditions.

Table 2: Comparison of proposed network with other state of the art.

Methods	**Dice score**
Patravali et al., 2018[27]	0.95(ED), 0.90(ES)
Isensee et al., 2018[28]	0.945
Budai et al., 2020[8]	0.927
Yang et al., 2019[29]	0.919
Li et al., 2019[30]	0.942±0.055 lvc
Simantiris & Tziritas, 2020[14]	0.967 (LV)
Proposed	**0.978(ED), 0.92(ES)**

We have compared our results of LV segmentation with other methods for ACDC dataset as shown in table 2. The proposed network perform very well and achieve 0.97(ED) & 0.92 (ES) dice scores for LV segmentation. J. patravali et. al.[27] used Unet architecture to locate LV cavity and achieved 0.95(ED) and 0.90(ES) dice score. Isensee F. et.al.[28] proposed Unet architecture for LV segmentation and got a 0.945 dice score. Adam Budai[8] used RESNET34 with dense block to extract LV cavity and got 0.927 Dice score. Fan Yang et. al.[29] developed Unet with residual block model to segment LV cavity and achieved a 0.919 Dice score. Zhongyu Li et. Al.[30] proposed Deep layer aggregation network for LV segmentation and got a 0.942 Dice score. Georgios Simantiris et. al.[14] proposed dilated CNN to localize LV and got Dice score of 0.967.

From these experiments and results, we made some considerations for CMR segmentation for proposed method. First, there is lack of data to prevent Overfitting problems in medical segmentation. To solve this problems, data augmentation approaches is carried out by using affine transformation. Second, proposed network has located perfect boundaries of LV as compared to cardiologist for that slice which has the same pixel intensities in two different regions because of poor contrast. Third, model can work very well on mid phase slices, apical and basal slices. Four, the proposed network performs CMR segmentation accurately for more than one dataset.

Conclusion

In this paper, we proposed dense Unet architecture with LSTM and bidirectional convolution to reduce redundant information and extract more diverse feature information from the network layers. The proposed network was trained and tested on ACDC dataset for different phase instant of cardiac cycle with high dice scores compared to other methods. This proposed network gives remarkable Segmentation results for Multi-Disease Cardiac Image Segmentation Challenge (M &Ms) dataset that contains a variety of diseases case hence proving its robustness. The proposed network performs very well on poor contrast and slices with papillary muscles in LV cavity hence proving its effectiveness. This network segment apical and basal slices with high dice score

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