Automatic Segmentation of Left Ventricular Endocardium and Epicardium from Cardiac Cine MRI Using Deep Learning

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Abstract
This research work uses cardiac cine magnetic resonance imaging (MRI) and deep learning (DL) methods to focus on automated left ventricle epicardium and endocardium segmentation. Using left ventricle segmentation, researchers have already established novel image analysis methods. The literature review aims to contextualize fundamental concepts that, while technical, impact cardiac MRI diagnostic capabilities. Recent advancements in cardiac MR imaging have rekindled interest in MR in radiology and cardiology. The method employs multi-channel DL to segment LV endocardial & epicardial structures. To ensure segmentation accuracy and durability, multi-channel DLsegmentation contours were merged into a level-set formulation targeting annular shapes. The Dice coefficient was utilized to compare manual delineation to segmentation results. Human and machine segmentation overlap was compared using dice values. Manual and automatic segmentation agreements improve with dice value. In terms of segmentation performance as well as average Dice coefficient for LV endocardial & epicardial borders, the suggested method performs better manual segmentation in general. It also outperforms DLand level-set manual segmentation techniques.
Keywords: Segmentation, Automatic Segmentation, Deep Learning, Left Ventricle, Endocardium, Epicardium, MRI
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Abbreviations

- CNN: Convolutional Neural Network
- LGE: Late Gadolinium Enhancement
- LV: Left Ventricle
- MFCN: Multi-Channel Fully Convolutional Neural Network
- MRI: Magnetic Resonance Imaging
- ReLU: Rectified Linear Unit

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1. Introduction

1.1 Background of the Study

Coronary heart disease (CHD) as well as stroke are the main reason of morbidity and mortality worldwide.According to the Centres for Disease Control and Prevention [1] well almost 610,000 deaths occur from cardiovascular diseases(CVDs) in the United States each year. MRI, echocardiography (ECHO), computed tomography (CT), as well as nuclear medicine are used to detect, track, as well as cure CVD.

1.2 Magnetic Resonance Imaging (MRI)

Cardiovascular MRI is the fundamental basis for evaluating the heart's functionalities. In the past, two-dimensional cine-cardiograms were used to diagnose heart disease [2]. A sequence of breath-holds is conducted in conjunction with MR imaging to determine the cause of the problem. Specifically for image post-processing [12]. This results in a strong contrast between the blood and myocardium as well as a decrease in the artefacts caused by breathing motions during the image capture process.

1.3 Automatic Left Ventricle (LV) Segmentation

The development of a computer-aided approach for cardiac segmentation that is efficient, reliable, and reproducible is highly sought to replace human contouring. Furthermore, DL-based strategies may require a set of training data (TD) in order to perform automated LV segmentation.Studies conducted [3] aimed to propose a mechanism for trustable and automated LV segmentation that combined previous information-based level-sets with DL and could be used efficiently and widely in medical practice without a large amount of TD.

1.4 Aim and Objectives of the Research

1.4.1 Aim of the Study

The foremostaim of this research work is to investigate the automatic segmentation of the epicardium and endocardium of the LV using a DL algorithm and cardiac cine MRI.

1.4.2 Objectives of the Study

- To review the literature regarding the automatic segmentation of LV epicardium & endocardium.
- To discuss the usage of cardiac cine MRI in the automatic segmentation process.
- To analyse the use of DLalgorithm in the cardiac cine MRI scanning technique.

2. Literature Review

2.1 Introduction

Treatment of heart problems necessitates the diagnosis of anomalies in the left ventricle through cardiovascular MRI. Automatic LV segmentation systems have been investigated in the literature [4] to deliver more accurate findings in a shorter amount of time. In the past, various studies [5] have developed a novel technique that exploits the distinct segmentation of the left ventricle to process pictures individually rapidly. Pre-processing improves and enhances the image's quality by adjusting the mean contrast. The layers of the endocardium and epicardium are segmented using a distinctive MTAC (Morphological Tuning with Active Contours) segmentation method [10], which results in a satisfactory and preferred segmentation.

New progress in heart MRI have focussed attention on the technology's potential, and it proceeds to attract the interest of both cardiologists as well as radiologists. With improvements in speed, picture quality, durability, and range of application, cardiac MRI is becoming more widely recognised as a useful diagnostic instrument. The review of the literature [7] contains many of the significant achievements which have contributed to the present condition of cardiac MR and efforts to contextualise some ideas that, while technical, have a meaningful effect on cardiac MRI diagnostic power. Numerous studies [8] cover myocardial viability & perfusion image analysis, flow quantification, functional imaging, as well as coronary artery imaging, among the issues covered in numerous research [8].

2.2 Past Studies

Previously published studies [9] coupled DL and level set to develop a distinctive system for automatic LV segmentation utilising cardiac cine MR data.When the visual component of interest has a great number of structure as well as visual appeal variation, this relationship works well for segmentation problems.Nonetheless, the annotated TD is small, as is common in medical image analysis.For example, level set strategies focus on form and appearance words and require minimum training sets but have limits for describing visual item variability. While DL systems may catch such changes with very little annotated training, they generally need regularisation to achieve effective generalization. Consequently, combining two strategies boosts the benefits of both approaches, resulting in a system that requires minimum training sessions and gives consistent segmentation results.

Numerous DL methods have been applied to segment the heart in the literature. Authors Koo et al. [4] offered strategies for segmenting and assessing the LV using deep multitask learning. Tan et al. [13] used a fully CNN [11] to study the LV endocardium. The researcher built and implemented an anatomically constrained neural network to enhance as well as segment cardiac images. To distinguish cardiac images, researchers used a CNN algorithm with a shape. To discriminate between the left and right ventricles, Xue et al. [25] suggested multitask DL approach with form refinement (RV). Irshad et al. [10] used CNN with a loss function and an active contour model to segment the LV and RV.Using a deep neural network, Irshad et al. [10] assessed cardiac MR images. Habijan et al. [26] had been using a CNN approach to calculate LV volume as part of an integrated inquiry involving multiple distributors as well as places.

Tan et al. [13] advocated segmenting the LV endocardium and the RV using the usual level set approach utilizing CNN-provided starting outlines. Dabiri et al. [14] used machine learning (ML) and level set approaches to segregate the LV endocardium. They used the LV endocardial contours as the beginning contours for segregating the LV epicardium. The deformable or level-set technique [15], the registration model [17], the clustering technique [16], the atlas model [18], as well as the DL method [6] have mostly been submitted earlier for segregating the LV on cardiac cine MR images. While most algorithms that employ shape priors achieve acceptable performance, their robustness is heavily reliant on the initial contour.

Variation in image intensity is a critical obstacle for image segmentation in cardiac MRI [19]. Using the image's structured dependence to provide the relatively similar class labels to close spatial & structural pixels is one useful method for overcoming this. It is feasible to achieve this with the aid of a deep CNN [11]. CNN's hierarchical feature representation, in particular, is resistant to major appearance fluctuations. Even though, because of the feedforward structure's spatial pooling, CNN may cause spatial blurring. The FCN [20] has the capacity to appropriately solve this issue. For the heart ventricle, we showed that utilising MFCN in combination with an annular form level-set greatly increased structural identification accuracy and consequently complimented existing local structure-based segmentation approaches [22].

2.3 Mapping Techniques

The standard for assessing chronic MI is late gadolinium enhancement (LGE) MRI [21]. However, adding LGE MRI into an MRI evaluation increases scan length and raises safety questions. Even though LGE MRI is not recommended for individuals with severe kidney disease, patients with normal renal function could accumulate gadolinium in their epidermis, dentate nucleus, and globus pallidus. It would be excellent if a gadolinium-free contrast agent could be utilised to identify and define MI consistently. MRI feature tracking, on the other hand, is a technique which distinguishes among regional myocardial morphology as well as aberrant ventricular wall motion affected by MI using non–contrast–enhanced cardiac MRI generated as component of a basic cardiac MRI evaluation.Although these tests are limited to establishing the MI's existence and location, they could be further impeded if time-consuming post-examination processing is necessary.

2.4 Deep Learning

Deep learning algorithms for picture segmentation have been presented in the literature [5] to extract complex forms from training data. To obtain stable and viable results, it is critical to use a large amount of training data. Despite the fact that the level-set approach is not training-dependent, the shape model is too simple to give an explanation for all physiological deformations.In spite of this, the annotated TD is small, as is common in medical image analysis. The framework for DL is as follows:

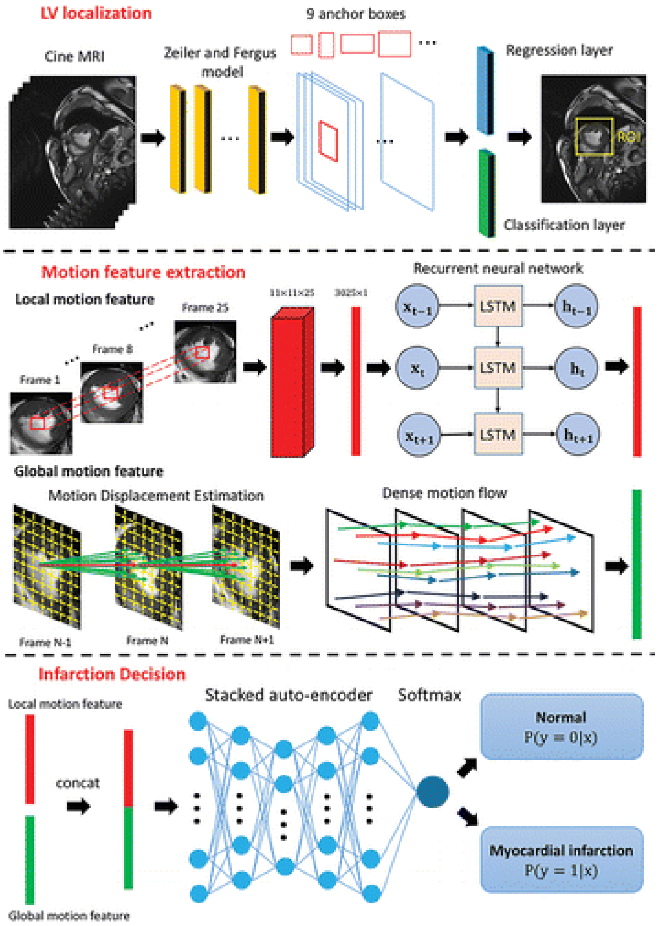

Figure 1: DL Algorithm

To detect the left ventricle, a deep neural network was employed, which contained components for obtaining both local and global motion data and discriminating between MI and normal myocardium. Finally, a fully linked discriminative network was employed to detect the difference between MI and normal myocardium.

2.5 Automatic Segmentation

The following figure depicts the segmentation scheme and automated representative segmentation utilized in the proposed modified UNET technique [8]. The altered UNET method is shown with a segmentation scheme as well as automated representative segmentation.

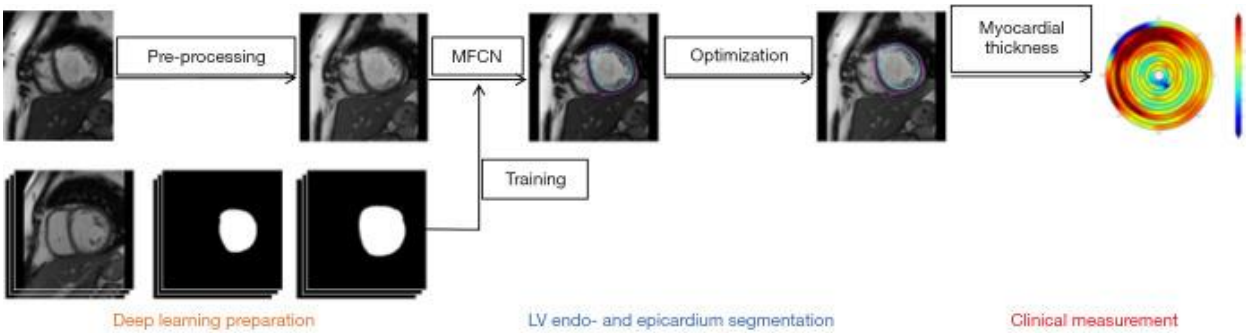

Figure 2: Schematic illustration representing the modified UNET technique for segmenting the left ventricle's epicardial and endocardial outlines.

Tran [20] directed an MFCN on the TD to segregate the LV endocardial and epicardial contours concurrently that used a U-net-based MCFN (multi-channel fully convolutional) neural network.In comparison to the endocardial contour, which separated the greater signal densities of blood from the weak signal densities of the heart, an epicardial area was a dissipate entity with weaker particularly in comparison to neighbouring tissues.To alter the segmentation study outcomes, the segmented contours from MFCN were seen as an MFCN-based appearance term all through the level-set technique. Similar to annular both endocardial & epicardial contours were determined using 2 elliptical contours to improve the last segmentation. As a result, an effective and stable boundary delineation was achieved. The endocardium and epicardium of the LV were segmented to determine the myocardial width. The study's analysis [20] outlined the procedure in great detail.

2.6 Statistical Information

Previous research has demonstrated that certain modest modifications in medical imaging can occur. For example, deep neural networks can discern anomaly progression with more precision and sensitivity than human eye assessment [23]. According to research [7], myocardial wall motion can be used to predict the position of chronic MI using DL. For sensing chronic MI, the DL method has high sensitivity, selectivity, as well as AUC. The research framework in [24] might compress distribution of local motion while obtaining the global motion area from a time - series data from a selected area, as well as generate a high - density motion field able to robustly classifying both global & local movements.

Another study [8] used derived motion data to create a fully autonomous DL system for detecting chronic myocardial infarction (MI) in non-enhanced cardiac cine videos. The suggested DL method was capable of identifying chronic MI's existence, transmurality, place, as well as dimensions without any extra information from LGE images, as per the Dice score, as well as correlations between chronic MI segmented from non-enhanced cardiac cine images and those manually defined on LGE images. Subendocardial MIs had a lower overall sensitivity than transmural MIs, which the researchers attributed to their greater circumferential strain. This work adds greatly to the body of knowledge by proving that routinely recorded non-enhanced cardiac cine pictures may diagnose chronic MI.

2.6.1 Summary

In sick people with myocardial failure, LV function is a good determinant of prognosis, and ventricular volume as well as mass are linked to myocardial illnesses like infiltrative ailments, hypertrophic cardiomyopathy, & ischemic cardiomyopathy affected by coronary artery disease.To achieve the manual segmentation challenging problem, appropriate LV segmentation assessment is useful for medical application, and repeatable information is required. Using DL to examine left ventricular volumes and function totally automatically is possible, fast to do, and exhibits acceptable performance without the need for manual modifications. Even if human tweaks are necessary for exact findings, this procedure is still quicker than manual analysis.

A restriction of previous research is that all training as well as testing was done with observational studies, whilst its evidence from clinical use in clinic still needs to be measured, particularly on datasets with a wider range of cardiovascular anomalies and imaging artefacts. Moreover, because different observers documented both the testing and training sets, the CNN's results in terms of interobserver variations are still to be extensively assessed.

3. Material and Methods

3.1 Introduction

The researcher worked on segmenting the endocardium and epicardium from the left cardiac ventricle. The research employs cardiac MR images, with the endocardium and epicardium being segmented from only the LV portion. Concentrating on the LV rather than the right is that the research's scope is restricted to the same.

3.2 Segmentation Architecture

Several recent studies have looked at the prospects of merging machine learning with level-set approaches in order to minimise the number of training datasets necessary for cardiac MRI segmentation. However, these methodologies usually require extensive training datasets in order to develop a general model capable of completing reliable LV segmentation. Small sets of data introduced significant bias, reducing the precision of such algorithms, particularly when the structure of the heart differed from TD, as in post-infarct remodelling as well as congenital heart disease [12].

In particular, the work was segmenting the epicardium and endocardium from the left ventricle’s cine-MRI images. For segmenting the two portions, the approach was to use a DL architecture, and in that, the UNET architecture is used because it is a popular tool for segmentation. The combination of multi-channel, fully CNN, as well as annular shape level-set algorithms utilised by UNET successfully segments cardiac cine MR images. This research work used a modified UNET architecture for the segmentation of left ventricles. The segmentation task is trained using a multi-channel DL algorithm with the objective of retrieving the LV endocardial and epicardial contours.

3.2.1 Loss Functions

The models have been have tested by considering two different loss functions:

- BinaryCross Entropy (BCE)

For every random variable or sequence of events, "cross entropy" is the difference in probability distributions between two unique distributions. It is often used for classification purposes, and it works well since segmentation demands pixel-level categorization. Binary cross entropy [28] is a loss function for binary classification applications. The BCE is a very straightforward approach to train a model to concurrently solve numerous classification concerns if each classification can be reduced to a binary choice. An image classification model's performance is evaluated and quantified using the cross-entropy loss [27]. The BCE is a subset of the cross-entropy class. It offers forecasts using deep neural networks and sigmoid activation. This is the default loss method, which is generally used for most DL architectures.

- Dice Loss

Computer vision researchers commonly apply the Dice coefficient to evaluate the degree of similarity between two images. Later, during the year 2016, it evolved as a loss function called Dice Loss [29]. Due to the non-convex character of the Dice Coefficient, it has been altered to make it more tractable. The dice parameter is related to segmentation because it works on overlapping.

The loss function in DL is used to measure the performance of any DL model. It measures how well a DL model performs a particular task. Along with the Binary Cross Entropy, this system architecture uses dice loss to analyse how the automated segmentation covers much overlap functionality over the manual. The dice loss is an important parameter for the segmentation model because the dice matrix represents the proportion of the automated segmentation part covering the manual part of the left cardiac ventricle.

3.3 Dataset

On the MICCAI 2009 LV challenge dataset, the models' performance was measured using dice performance measures. The 2009 LV challenge dataset from MICCAI features 45 investigations into the heart, each with a different condition. Heart failure with myocardial scarring, heart failure without myocardial scarring, heart failure with hypertrophy, as well as normal cardiac function is all covered in this research. All of the patients in this dataset got 1.5T MRI scans of their hearts. The following scan parameters were reported in the dataset for breath-hold 2D cine images:

- matrix =256×256
- 20 cardiac phases
- FOV =320×320 mm2
- 6–12 short-axis slices
- thickness =8 mm

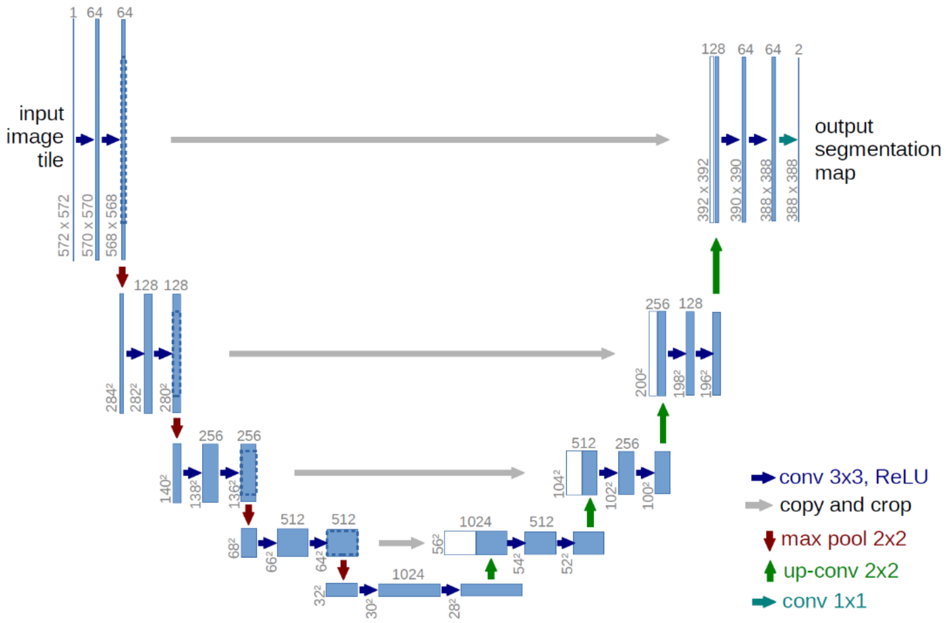

Figure 3: UNet Network ArchitectureDiagram

The UNet network design is depicted in the above diagram. It has two pathways, one shrinking and the other growing. The contracting path is typical of convolutional networks. For 2x2 max, pooling with stride 2 and two 3x3 convolutions followed by a rectified linear unit are utilized for down sampling (ReLU). At the end of each convolution, batch normalisation is performed, and at the end of every two convolutions, the dropout is performed after the batch normalization.

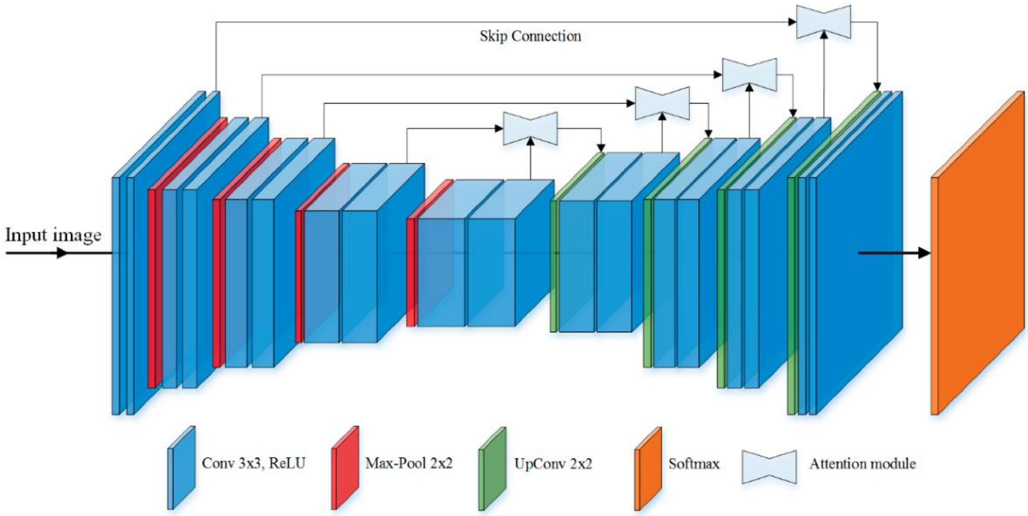

Figure 4: Illustration of the single-channel FCN and U-net topologies used to show the suggested multi-channel FCN network

Since the analysis of the literature suggests that the lower the kernel size, the better. Therefore, the size of the kernel is 3x3 in this system architecture, and the activation is ReLU. This helps in capturing the low-level features of the MR images. The maximum pooling (max pooling) size is 2x2, which halves the MR images. Moreover, in the reverse process, the up convolutional (Up-Conv) part is also 2x2, which helps put the segmentation image back. The output is the final image with the segmented region. To verify and compare whether the segmented image has been regenerated with the original image, the dice parameter measures how efficiently the up-conv has been done. If the dice value is greater, then the segmentation has been obtained correctly.

The number of feature channels is doubled when down sampling is used. The substantially concatenated feature map from the expanding path is concatenated with a convolution (up-convolution) of the correspondingly cropped feature map from the contracting path, and then two 3x3 convolutions are each accompanied by a ReLU in the expanding path. This is because each convolution loses boundary pixels. A 1x1 convolution classifies each 64-component feature vector. This network contains 23 layers. Use an input tile size big enough to apply all 2x2 max-pooling procedures to a layer when creating the output segmentation map.

3.4 Phases

Two main stages have been proposed in this system architecture. These are:

- Training Stage
- Testing Stage

The initial training stage is to train the model for segmentation. Whenever an image is fed into a trained model, the output recognizes the segmented area by masking the rest of the image. During the training stage of the presented architecture, two images are input with manually labelled segmentation and passed through the system.The cardiologists perform manual segmentation of these images and are given in the dataset as ground truth [30]. Following that, a comparison is made between the manually segmented image as well as the automatically segmented image, and a score is determined by calculating the various variables described earlier. Later, based on the ground truths in the dataset, the testing of the efficacy of the trained model is performed.

3.5 Implementation

The neural network was created in Python using Tensorflow [31] for the training. OpenCV has been used for image processing. To begin with, a CNN was created. Furthermore, a number of variables were used to evaluate the CNN's effectiveness. During the final segmentation, the dice metric was applied to evaluate and fine-tune the recommended model. An optimizer is part of deep learning. The optimizer updates the weights and learning rates of any DL model.

The hardware configuration was as under:

- Processor: Intel Xeon
- RAM: 32GB
- GPU: 8 GB

3.6 Summary

The above analysis discussed the study's utilisation of a technology named "modified UNET." UNET efficiently segments cardiac cine magnetic resonance (MR) pictures by mixing multi-channel, fully CNN with annular shape level-set algorithms. To summarise, the strategy uses a multi-channel DL algorithm to train segmentation in order to extract LV endocardial and epicardial morphologies. Next, the multi-channel DL approach's segmentation contours were combined into a level-set composition designed to recognize annular formations, ensuring the correctness and reliability of segmentation. The segmentation results were compared to a manual delineation reference standard using the Dice coefficient. Dice values were applied to determine the overlap between human and machine segmentation. There was a correlation between dice values and manual as well as automatic segmentation accuracy.

4. Results and Discussion

4.1 Introduction

DL algorithms for image segmentation have been presented in order to infer complex forms from training data. On both testing & training datasets, the recommended automatic technique was evaluated. Image segmentation is hindered by the fast shift in image intensity that happens during cardiac MRI. Using the image's structured dependence to supply the relatively similar class labels to close spatial as well as structural pixels is one useful method for combating this. Deep CNN was used to accomplish this in the system.

4.2 Observation and Evaluation

The segmented contours of MFCN were being used as beginning contour and as an appearance term in the energy function of the Level Set technique, and the segmented contours of MFCN were used as the ending contour. It was important to consistently identify the LV with close contours in the LV using a modified UNET that was capable of improving segmentation from MFCN's segmented contours. As a result of the vast quantity of data required for the training set, it was necessary to employ a significant number of TD in order to get consistent results. In this study, reliable segmentation was attained using DL and level-set methods with a restricted training dataset.

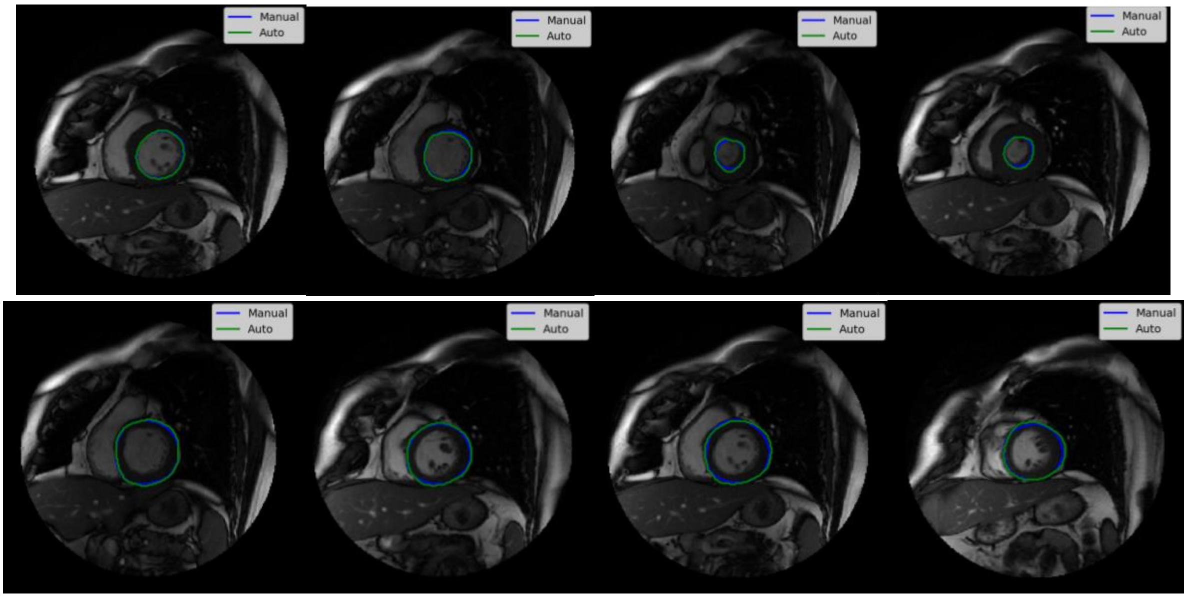

Figure 5: Segmentation of the LV endocardium and epicardium using Binary Cross Entropy. The proposed optimization approach yielded green lines, however the manual delineation produced blue lines.

The preceding image shows the recommended altered UNET method and manual segmentation outcomes for one instance on 7 specimen slices using the BCE function. The green and blue lines indicate the suggested automatic segmentation approach and manual segmentation results, respectively. The recommended modified UNET technique efficiently segmented icontours and ocontours, resulting in outcomes on par with those obtained by manual delineation, as shown in the figure. The icontours show the LV endocardium, and the ocontours show the LV epicardium segmentation images.

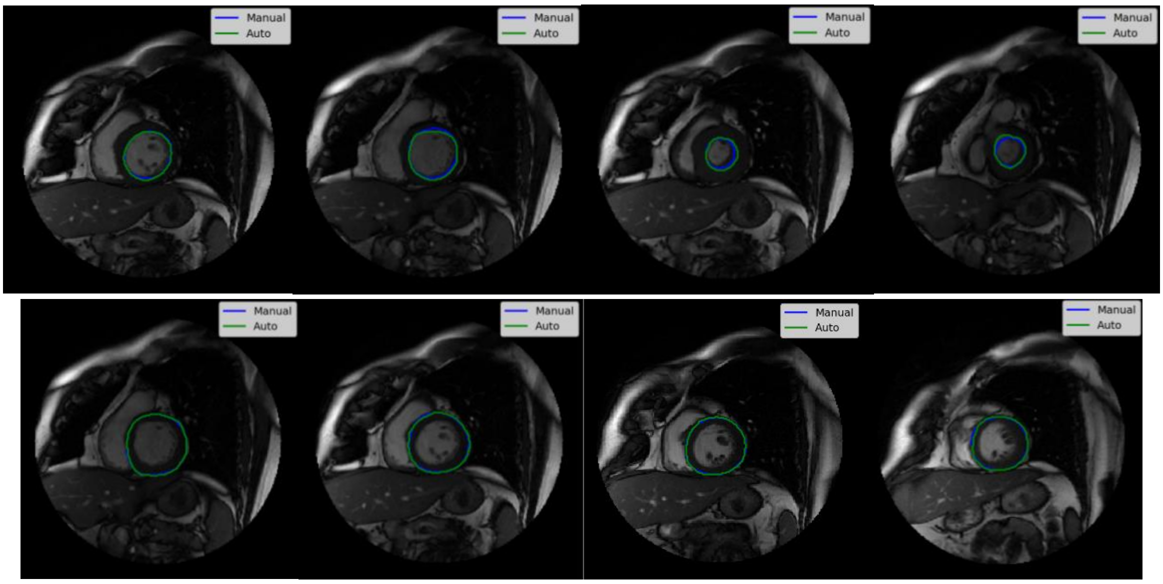

Figure 6: Dice Loss segmentation of the left ventricular endocardium and epicardium. The proposed optimization approach yielded green lines, however the manual delineation produced blue lines.

The above figure illustrates the proposed modified UNET algorithm as well as manual segmentation outcomes for 7 typical slices using the Dice Loss function. The green and blue lines indicate the suggested automatic segmentation approach and manual segmentation results, respectively. The recommended modified UNET technique efficiently segmented icontours and ocontours, resulting in outcomes on par with those obtained by manual delineation, as shown in the above figure. The icontours show the LV endocardium, and the ocontours show the LV epicardium segmentation images.

$$Dice\% = \frac{2|R_A \cap R_M|}{|R_A| + |R_M|} \times 100$$

Table 1: Binary cross entropy and Dice values for LV endocardium and epicardium delineation

Method	Loss Function	Endocardium	Epicardium
Existing Approach	Binarycrossentropy	92.03	93.95
Proposed Approach	Dice Loss	93.24	94.76

As shown in the above table, the combined multi-channel DL and annular shape level-set segmentation method outperformed manual segmentation with average BCE and Dice values for LV endocardium and epicardium delineation due to the Adam optimizer.

Table 2: State-of-the-art comparison between manual delineations

Dice Coefficient	Endocardium	Epicardium
Schaereret al. [32]	0.87	0.92
Zheng et al. [33]	0.88	0.94
Constantinides et al. [34]	0.89	0.92
Queirós et al. [35]	0.90	0.94
Avendi et al. [36]	0.94	-
MFCN Approach	0.92	0.94

For segmenting LV from cardiac MRI, manual delineation continues to be the gold standard. Manually segmenting the LV in 2D slices, on the other hand, takes a long time, is complex, and is prone to human mistakes due to exhaustion. The use of MFCN in conjunction with the annular form level-set improved structural detection performance in the heart ventricle, supplementing previously used local structure-based segmentation methods.

4.3 Discussion

Comparatively, the epicardial area is a diffuse entity with minimal distinctiveness when compared to its neighbouring tissues. As a result, traditional signal intensity-based segmentation algorithms struggle to segment signals; on the other hand, systems that use prior knowledge or are based on DL may have less difficulty segmenting signals. Because it has higher contrast than the rest of the heart, endocardial segmentation has a high precision, which is highly impacted by the accuracy with which the papillary muscles are traced. The irregular shape of the endocardial trabeculations is detected. In this experiment, the epicardium scored higher on the Dice scale than the endocardium or coronary arteries because of using the segmentation method described above.

4.4 Summary

As demonstrated by the literary works, fully automated cine MRI processing systems relying on CNNs have been constructed as well as evaluated in a relevant context using heterogeneous information from patients with CVD obtained from several distributors as well as numerous centres.As per the research results, a DL CNN can reliably understand as well as segment the LV in real-time, producing closely correlated volumetric metrics as well as correct LVEFs that are comparable to those generated by knowledgeable spectators, all without requiring any user interaction.These results show that our method can accurately detect modifications in the LV myocardium all through the cycle of the cardiac.The learning-based segmentation technique used during gated MPS imaging has a lot of medical assurance.

The results as well as evaluation of the results demonstrates that the suggested method is better, with segmentation performance similar to manual segmentation as well as a Dice coefficient for the LV endocardial & epicardial borders which is greater than manual segmentation. The data also imply that the suggested strategy outperforms manual segmentation techniques such as deep learning, level-set, etc.

5. Conclusions

Manual LV segmentation is a time-consuming as well as sensitive procedure which differs depending on the patient, MRI, as well as experts.Even today, the manual delineation created by specialists is believed to reflect the underlying reality. As a result, the research presents a technique that employs CNN's to automate segmentation while simultaneously increasing accuracy. Using a wide range of MRI sets of data, the researchers introduced a technique for fully automated segmentation of the LV endocardium & epicardium. In addition to these, the system was also trained and evaluated concerning the architecture and a range of other characteristics. The researchers found a significant improvement in precision and robustness when the results were compared to the reference method and other accurate procedures. Because of this, CNN's hierarchical feature representation, in particular, is resistant to significant appearance variations.

Although this was the case, the existing research had some limitations. It is necessary to manually count the slices covering the heart since it travels longitudinally during the cardiac cycle. The amount of slices surrounding the heart may change as the patient progresses through the cardiac cycle.To improve the latest research, a method for automatically determining the slices that used a 3D neural network as well as a 3D level-set method will have to be formed in the long term.

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