Segmentation of Myocardium in Left Ventricle using Deep Learning Techniques to determine Wall Thickness

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***Abstract*— The segmentation of the myocardium in the left ventricle plays a very important role in evaluating cardiac health, as myocardial wall thickness offers significant insights into various cardiac conditions. This study delves into how deep learning techniques can be utilized for automating the segmentation process, enabling precise wall thickness measurements. Utilizing the Automated Cardiac Diagnosis Challenge (ACDC) dataset—a comprehensive collection of annotated cardiac magnetic resonance (CMR) images—this research develops and evaluates a U-Net-based Convolutional Neural Network (CNN). The dataset comprises diverse cardiac states and presents challenges like variable myocardial boundaries and heart size discrepancies. The proposed framework addresses these challenges, ensuring reliable and accurate segmentation to assist in clinical evaluations.**

Keywords—Myocardium, Left Ventricle Segmentation, Wall Thickness, Image Segmentation.

I. INTRODUCTION

Analyzing the structural and functional aspects related to heart requires accurate segmentation of cardiac components such as the myocardium and left ventricle. Among the radiology modalities, cardiac magnetic resonance imaging (MRI) is widely regarded for its high-resolution capabilities, enabling detailed assessment of myocardial wall thickness. These measurements are instrumental in diagnosing cardiovascular abnormalities. Traditional segmentation approaches often depend on manual annotations by clinicians, which are labor-intensive and subject to variability among observers. The evolution of machine learning models, especially the development of convolutional neural networks (CNNs), has enabled automated approaches that significantly improve the accuracy and reliability of image analysis. This study adopts the U-Net architecture, a specialized design for image segmentation tasks, which integrates an encoder-decoder framework with skip connections to preserve spatial details and improve boundary detection. Leveraging publicly available annotated datasets, the proposed approach automates the segmentation of endocardium and epicardium layers, facilitating precise myocardial wall thickness evaluation. This automation reduces the burden of manual efforts and offers robust clinical insights, underscoring its potential for real-world healthcare applications.

II. LITERTURE SURVEY

Irmawati et al. [1] introduced an advanced neural network-based approach for the segmentation of both the ventricles in cardiac MRI images. The approach incorporated publicly available datasets like ACDC and MICCAI to improve segmentation accuracy and reduce computational load through region-of-interest localization techniques. They combined CNN architectures with deformable models, including the double snake method, to enhance boundary delineation. Furthermore, advanced modules such as Deep Layer Aggregation (DLA) and Refinement Residual Blocks (RRB) were integrated to improve performance, demonstrating suitability for clinical diagnosis.

Lim et al. [2] investigated the impact of segmentation techniques and software on myocardial strain quantification in CMR images. Their findings highlighted how variations in slice selection methods and post-processing protocols influence strain measurements, emphasizing the need for standardized workflows for reliable clinical assessments.

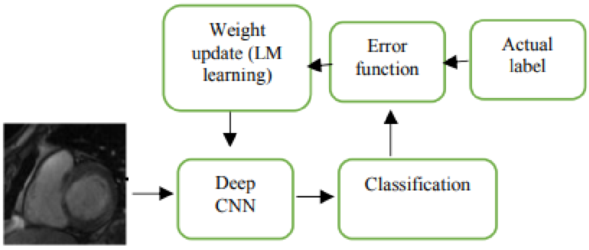

Fig 1. Framework of Classification using LM Learning

Deepa Krishnaswamy et al. [3] introduced a novel 3D-to-3D diffeomorphic registration algorithm aimed at segmenting. The left ventricle in cardiac MRI imaging (MR) and ultrasound (US) imaging. The proposed method computes voxel-to-voxel correspondences across three-dimensional space, parameterized by radial and curl components to accurately model cardiac deformations. Constraints are applied to control the extent of deformation, ensuring anatomically plausible transformations. The algorithm was evaluated on the ACDC MRI dataset (521 frames from 20 patients) and a US dataset (213 frames from 10 patients). Compared against six established registration methods, including Symmetric Normalization (SyN) and Elastix, the proposed method achieved superior Dice scores of 98.10% for MRI and 92.90% for US, while maintaining a zero percent mesh folding rate. These results highlight its robustness across imaging modalities and diverse patient conditions, making it a reliable tool for clinical cardiac assessments.

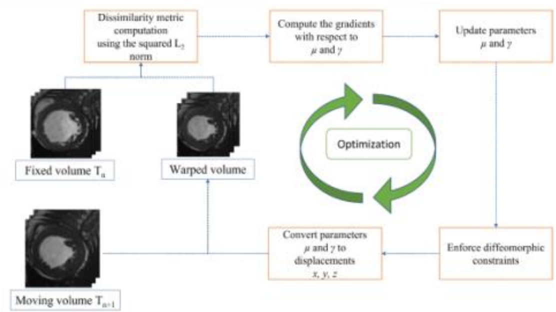

Fig 2. Components of 3D-to-3D diffeomorphic image registration algorithm

Amjad Khan et al. [4] reviewed segmentation methodologies for cardiac MRI, categorizing them into manual, semi-automatic, and fully automatic approaches. They evaluated models like active shape and contour-based methods, alongside CNN-based techniques, identifying challenges such as identifying abnormal tissues in contrast to healthy myocardium. The review underlined the importance of statistical validation and proposed advancements to enhance segmentation precision.

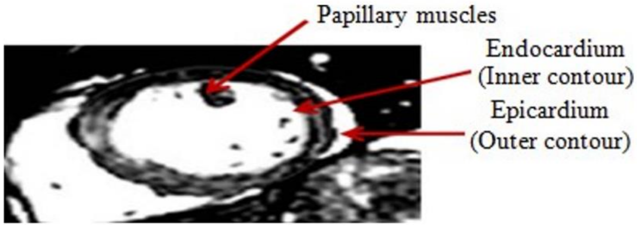

Fig 3. Anatomical view of LV short-axis image

Ziyue Wang et al. [5] introduced MMNet, a multi-scale neural network designed to completely automate left ventricular division of regions in cardiac magnetic resonance imaging (MRI). The proposed system addresses challenges such as blurred ventricular edges, variability in ventricular shape, and end-systolic segmentation inaccuracies. MMNet innovatively combines a multi-scale feature fusion module with dilated convolution to enhance edge information and employs full-size skip connections to integrate features across different layers. Additionally, a pre-activation module mitigates overfitting and enhances gradient propagation. Extensive experiments on benchmark datasets demonstrate that MMNet achieves superior segmentation accuracy, outperforming traditional models like UNet and FCN. Key metrics such as the Dice coefficient and Hausdorff distance validate the effectiveness of MM Net, making it a robust and efficient tool for clinical cardiac image analysis. The model primarily uses Dilated Convolution, whose major formula is,

$$F *_d f(p) = \sum_{s+d\cdot t=p} F(s) f(t)$$

where,
F represents the input feature map,
f the filter
d the dilation rate
This enables multi-scale feature extraction without additional computational cost.

Caroline Petitjean et al. [6] presented A thorough evaluation and examination of segmentation techniques for short-axis Magnetic resonance imaging of the heart, focusing on the delineation of the two ventricular contours. The proposed system categorizes existing methods into weak and strong prior-based approaches, emphasizing the role of external knowledge, such as anatomical models and statistical shape models, in enhancing segmentation robustness. Techniques like deformable models, active shape models (ASM), and atlas-based approaches are reviewed in detail. The study highlights the challenges posed by myocardial complexity, inter-patient variability, and MR imaging artifacts. Numerical comparisons are conducted using metrics such as point-to-curve errors, Dice coefficients, and ejection fraction computations, illustrating the progress and gaps in this domain. The discussion concludes with trends in integrating motion modeling and machine learning into segmentation workflows, underscoring the need for improved automation and accuracy in clinical applications.

$$EF = \frac{V_{ED} - V_{ES}}{V_{ED}} \times 100$$

This equation calculates Ejection Fraction, where,
Ved is the end-diastolic volume
Ves is the end systolic volume

Wafa Baccouch et al. [7] states that in current clinical practices, myocardial viability assessment often relies on the subjective analysis of late gadolinium enhancement (LGE) sequences, which has the potential to result in inconsistent evaluations, especially in cases of partial scar transmurality (25%-75%). This paper introduces an innovative framework leveraging a deep convolutional neural network (CNN) for objective and quantitative myocardial viability assessment. The method utilizes automated delineation of the left ventricle contours via a modified U-Net architecture and regional myocardial wall thickness (MWT) quantification in multiple radial directions. A novel classification protocol integrates these parameters to differentiate viable and non-viable myocardial segments, addressing the challenges of peri-infarct areas. The outlined methodology was validated on a collection of data of 73 patients with myocardial infarction and 10 healthy controls, achieving an accuracy of 98.13%, sensitivity of 97.52%, and specificity of 99.09% ($p < 0.001$). The method significantly reduced inter- and intra-observer variability and showed promise in aiding clinical decision-making by minimizing unnecessary revascularization procedures. These results underscore the potential of integrating CNN-based frameworks into clinical workflows to improve diagnostic accuracy and optimize patient outcomes.

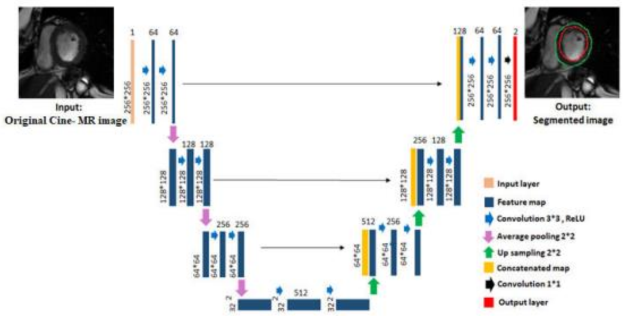

Fig 4. Neural Network architecture for automatic LV contours extraction

Fatemeh Zabihollahy et al. [8] discusses that Myocardial fibrosis (MF), a critical marker of various cardiac diseases, is commonly evaluated through late gadolinium enhancement (LGE) in cardiac magnetic resonance imaging (CMR). However, manual segmentation of myocardial fiber regions in LGE-CMR is labor-intensive and prone to inter-observer variability. This paper presents a machine learning-based framework for automated analysis and measurement of segmentation of MF, leveraging both conventional machine learning (ML) and advanced deep learning (DL) methods. The system employs CNNs and U-Net architectures to segment MF from 2D/3D LGE-CMR images. Advanced preprocessing techniques, including Enhancing data diversity through the application of generative adversarial networks (GANs) are employed to improve the model's generalizability. Experimental validation on diverse datasets demonstrates superior performance, achieving Dice Similarity Coefficients (DSCs) exceeding 90% for MF delineation. This fully automated approach shows promise in enhancing the precision of diagnoses while minimizing the need for manual intervention, and enabling precise assessment of risk and formulation of treatment strategies for cardiac patients. The Hausdorff distance is given by the formula given below,

$$HD = \max\left\{ \max_{a \in A} \min_{b \in B} d(a,b), \max_{b \in B} \min_{a \in A} d(a,b) \right\}$$

d(a,b) is the Euclidean distance between boundary points a and b.

Zhi Liu et al. [9] proposes a novel Multi-Constrained Segmentation (MC-Seg) method for the complete extraction of the left ventricle from cardiac MRI scans. By leveraging the U-Net architecture as a baseline, the system incorporates multi-task learning to integrate segmentation with cardiac parameter estimation tasks, such as cavity dimensions, myocardial areas, and wall thickness. These tasks serve as constraints to enhance network generalization and segmentation accuracy. The framework optimizes the segmentation through a blend of cross-entropy loss for segmentation and mean square error loss function for regression, achieving improved performance over state-of-the-art methods. Experimental results, validated on the MICCAI 2018 dataset with five-fold cross-validation, demonstrate the method's effectiveness with a Dice Similarity Coefficient (DSC) of 0.886. The MC-Seg approach provides clinicians with a reliable, automated tool for high-quality LV anatomical modeling and improved diagnostic interpretability. One of the several major metrics that is used here to compute the accuracy is Segmentation Loss (Cross-Entropy Loss), that computes the accuracy of predicted segmentation, which is given by,

$$L_{seg} = -\sum_{s=1}^{S}\sum_{f=1}^{F}\left[y_{s,f}\log\left(\hat{y}_{s,f}\right) + \left(1 - y_{s,f}\right)\log\left(1 - \hat{y}_{s,f}\right)\right]$$

Where:

- S = total subjects
- F = number of frames per subject
- $y_{s,f}$ = ground truth label
- $\hat{y}_{s,f}$ = predicted value for frame f of subject s

Jinchang Ren et al. [10] Accurate extraction of the myocardium and left ventricle regions from cardiac images is essential for the diagnosis of cardiac diseases and computational modeling of heart function. Traditional approaches face challenges in delineating fine boundaries and handling intensity similarities between areas of focus and surrounding tissues. This study introduces an innovative approach involving deep learning framework, the Multi-Task

Learning U-Net (MTL-UNet), designed to overcome these limitations.

The MTL-UNet integrates an edge detection module to enhance boundary precision and a fusion module to combine contextual and spatial features effectively. A weighted loss function, comprising Dice loss, cross-entropy loss, and edge loss, further improves segmentation accuracy by guiding the model to focus on critical boundary and region details. Evaluations on the ACDC 2017 dataset reveal that the MTL-UNet outperforms conventional segmentation models, demonstrating reliable and precise retrieval of the ventricles and myocardium. This work highlights the potential of advanced multi-task learning frameworks in addressing challenges in medical image analysis, offering significant improvements for cardiac segmentation tasks critical to personalized treatment planning. Future directions include exploring 3D extensions and enhancing the system's generalization to other medical imaging datasets.

III. TOOLS AND TECHNOLOGIES

Programming Language:

- **Python:** Python is a highly versatile programming language commonly utilized in machine learning and AI projects, thanks to its user-friendly nature, comprehensive libraries, and robust support for diverse data science applications.

Libraries:

- **TensorFlow:** A versatile open-source deep learning framework commonly used for developing and training neural networks. TensorFlow's support for GPU acceleration significantly improves the training time for the U-Net model used in this project. Its visualization tool, TensorBoard, aids in monitoring the process of training and model performance.
- **PyTorch:** Recognized for its flexible computational graph and ease of debugging, PyTorch is utilized for designing and training the U-Net architecture. The library's modular design allows seamless integration of custom layers, optimizers, and loss functions, essential for fine-tuning the model according to the particular needs of myocardial segmentation.
- **OpenCV:** OpenCV is applied for preprocessing the MRI images. Key functions include resizing adjust images to a uniform resolution, normalizing pixel intensities, and implementing filters to minimize noise. These steps enhance the quality of input data, ensuring the model gets standardized and clean images for segmentation tasks.
- **Matplotlib:** Matplotlib is applied to visualize results at various phases of the project. It equips with tools for creating plots, graphs, and overlays, which are essential for examining model performance and presenting the segmentation results. For example, segmented images with superimposed boundaries and thickness measurements are visualized using this library.
- **Numpy:** NumPy is central to numerical computations throughout the project. It is used for handling multi-dimensional arrays and matrices, which are fundamental to image data processing. Additionally, it enables efficient manipulation of pixel values during normalization and facilitates mathematical procedures needed to compute myocardial thickness.
- **Scipy:** SciPy supports advanced image processing and mathematical computations. Its ndimage module is applied for distance transformation, an important step in calculating the myocardial thickness by measuring the pixel distances between the epicardial and endocardial layers.
- **Pandas:** Pandas is employed for managing structured data, such as experimental logs and metrics. It simplifies the organization, manipulation, and analysis of training and validation results, ensuring efficient tracking of model performance across multiple iterations.
- **Scikit-learn:** This library is employed to assess the model's evaluation measures, such as accuracy and Dice Similarity Coefficient.

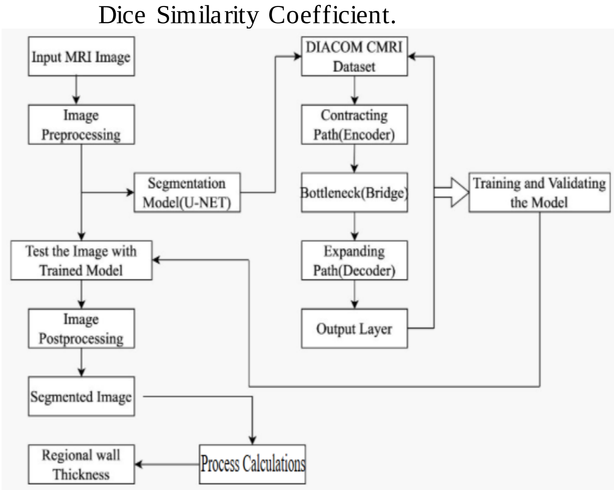

Fig 5. Architecture Diagram of the Proposed Model

IV. METHODOLOGY

A. *Method Overview*

This study employs a deep learning framework leveraging the U-Net architecture to streamline the process of segmenting the myocardium and left ventricle in cardiac MRI scans. The methodology comprises several key stages: data acquisition and preprocessing, model training, segmentation, and myocardial wall thickness determination.

B. *Data Acquisition and Preprocessing*

This study employs a deep learning framework leveraging the U-Net architecture to streamline the process of segmenting the myocardium and left ventricle from cardiac MRI scans. The methodology comprises several key stages: data acquisition and preprocessing, model training, segmentation, and myocardial wall thickness determination.

C. *Model Design and Training*

The U-Net architecture, known for its encoder-decoder design, was used due to its effectiveness in image segmentation tasks. The encoder extracts meaningful features, while the decoder reconstructs the spatial structure with fine boundary details. Skip connections bridge the encoder and decoder, preserving spatial resolution and improving segmentation accuracy.

The model was taught using data from annotated datasets using a combination of Binary Cross-Entropy Loss and Dice Loss as the optimization objectives. The Adam optimization algorithm was applied to adjust weights, and a dynamic learning rate scheduling technique was applied to enhance training stability. The effectiveness of the model was assessed through iterative testing to avoid overfitting.

D. Segmentation of Myocardium and LV

Upon completion of training, the U-Net model was applied to segment the myocardium and left ventricle from test MRI images. The segmentation process identified the inner (endocardium) and outer (epicardium) boundaries. Post-processing techniques, such as morphological operations, were used to refine boundary accuracy and eliminate noise from the results.

E. Wall Thickness Determination

Wall thickness was calculated by measuring pixel-wise distances between the endocardial and epicardial boundaries. The resulting thickness map provided a detailed visualization of myocardial thickness, facilitating precise regional assessments.

The myocardial wall thickness (T) at a pixel is computed as the difference between the distances to the epicardial boundary and the endocardial boundary:

$$T = D_{epi} - D_{endo}$$

Where:

D_{epi}: Distance of the pixel to the nearest point on the epicardial boundary.

D_{endo}: Distance of the pixel to the nearest point on the endocardial boundary.

V. RESULTS AND PERFORMANCE ANALYSIS

Segmentation: The segmentation model demonstrated robust performance in delineating the myocardium from cardiac MRI images. The U-Net's encoder-decoder architecture, complemented by skip connections, achieved high segmentation accuracy while maintaining fine-grained details. Preprocessing enhancements, such as normalization and noise reduction, improved input quality and contributed to precise boundary identification.

Quantitatively, the model achieved an average Dice Similarity Coefficient (DSC) exceeding 90% for both the left ventricle and myocardium. Measurements of wall thickness obtained from the model closely aligned with clinical ground truth values, further validating the reliability of the approach.

Thickness Calculation and Quantitative Performance: The calculated myocardial thickness and Dice Similarity Coefficients are displayed in a clear and concise manner using text boxes.

For each segmented cardiac MRI image, the system overlays the endocardial and epicardial boundaries on the original scan. Alongside this visual representation, a dedicated text box is used to present,

- Myocardial Thickness: The thickness values are calculated in millimeters, derived from the pixel distances between the inner and outer boundaries. These values provide a detailed assessment of regional variations across the myocardium.
- DICE Similarity Coefficient: This measure evaluates the precision of the segmentation by comparing the predicted boundaries with expert annotations. A high Dice coefficient (above 90%) confirms the reliability of the model.

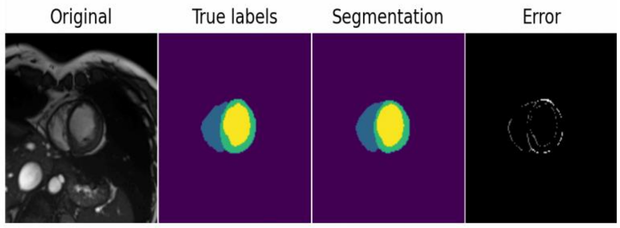

Fig 6. Sample of segmented output image

```
DICE Right Ventricle: 0.83414
DICE Myocardium: 0.83412
DICE Left Ventricle: 0.91972
2024-12-08 19:26:29.633 Python[5305:184368] +[IMKClient subclass]: chose IMKClient_Modern
2024-12-08 19:26:29.633 Python[5305:184368] +[IMKInputSession subclass]: chose IMKInputSession_Modern
Average Myocardial Thickness: 6.78 mm
```

Fig 7. Dice coefficients and thickness of the sample

Performance Analysis: The effectiveness of the suggested system was assessed using key metrics to assess the accuracy and dependability of myocardial segmentation and thickness measurement. The Dice Similarity Coefficient (DSC) was used as the primary metric for segmentation performance, measuring the overlap between the predicted and ground truth boundaries. The system consistently achieved DSC values exceeding 90%, demonstrating high precision in identifying the endocardial and epicardial boundaries.

The model's performance of the segmentation was assessed using metrics such as Dice Similarity Coefficient (DSC), which measured the agreement between the predicted segmentation and the reference ground truth annotations. The wall thickness measurements obtained from the model were tested against clinically established measurements to ensure accuracy and reliability.

DSC is a performance metric employed to assess the degree of overlap between the predicted segmentation(P) and the ground truth segmentation (G). It is provided by:

$$DSC = \frac{2 \times |P \cap G|}{|P| + |G|}$$

Where:

$|P \cap G|$: The number of pixels in the intersection of the predicted and ground truth masks.

$|P|$: The number of pixels in the predicted mask.

$|G|$: The number of pixels in the ground truth mask.

Here's some of the mean dice scores obtained after evaluating above specified sample.

Structure	Mean Dice Score
Left Ventricle (LV)	0.89
Myocardium (Myo)	0.82

VI. CONCLUSION

This study presents an efficient, automated solution for myocardial segmentation and wall thickness measurement using cardiac MRI images. By employing the U-Net architecture, the proposed system achieves precise boundary delineation with high Dice Similarity Coefficients, ensuring accurate segmentation. The integration of automated workflows minimizes manual effort and enhances the consistency of cardiac assessments, offering significant utility in clinical settings.

The system's efficiency in processing images within seconds makes it suitable for real-time clinical applications, reducing the workload on medical professionals and improving diagnostic workflows. Additionally, the integration of clear visual overlays and numerical results ensures that the outputs are both informative and user-friendly.

While the project demonstrates significant advancements, future work could explore the application of the framework to 3D imaging modalities and evaluate its generalizability to diverse datasets, further strengthening its relevance in medical imaging research and diagnostics.

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