International Journal for Modern Trends in Science and Technology
Volume 12, Issue 04, pages 925-931
ISSN: 2455-3778 online
Available online at: http://www.ijmtst.com/vol12issue04.html
DOI: https://doi.org/10.5281/zenodo.19644342

Deep Learning Segmentation of Cardiac MRI for Detection of Diabetic Cardiomyopathy Phenotypes

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To Cite this Article
Dr. A. Ramamurthy, Chinta Baby Srikari, Bogadhi Hemanth Suresh, Gangiredla Mahendra & Chandadi Joshua (2026). Deep Learning Segmentation of Cardiac MRI for Detection of Diabetic Cardiomyopathy Phenotypes. International Journal for Modern Trends in Science and Technology, 12(04), 925-931. https://doi.org/10.5281/zenodo.19644342

Article Info
Received: 17 March 2026; Revised: 07 April 2026; Accepted: 10 April 2026.

KEYWORDS

Diabetic Cardiomyopathy, Cardiac MRI Segmentation, Attention-Residual U-Net, Deep Learning, Myocardium Segmentation, Dice Similarity Coefficient.

ABSTRACT

Diabetic cardiomyopathy is a diabetes-related cardiac condition characterized by gradual structural and functional changes in the myocardium, which are difficult to identify through manual analysis of cardiac magnetic resonance imaging (MRI) [7]. Existing deep learning–based cardiac MRI segmentation approaches primarily focus on anatomical segmentation and often rely on complex preprocessing or edge-based methods, limiting their clinical relevance and robustness [2]. In this project, an improved deep learning framework is proposed for automated cardiac MRI segmentation to support the identification of diabetic cardiomyopathy phenotypes. The proposed system employs an Attention-Residual U-Net (AR-U-Net) architecture, which enhances the conventional U-Net [1] by incorporating residual convolutional blocks [3] and attention mechanisms [4]. This design enables the model to focus selectively on clinically important cardiac regions, particularly the myocardium, while reducing dependency on handcrafted edge detection techniques. The model performs segmentation of major cardiac structures, including the left ventricle, right ventricle, and left ventricular myocardium, using 2D short-axis cardiac MRI slices. Performance is evaluated using Dice Similarity Coefficient (DSC) and Hausdorff Distance (HD95). The approach demonstrates improved robustness, segmentation accuracy, and clinical interpretability with scope for future extension into 3D and temporal cardiac modeling. In addition to segmentation, the system integrates the LLaMA via the Groq API to generate detailed medical reports. A Retrieval-Augmented Generation (RAG) approach is used to incorporate relevant medical knowledge, enabling the system to provide clinically meaningful insights such as findings, diagnosis, and treatment suggestions.

1. INTRODUCTION

Diabetic cardiomyopathy (DCM) is a distinct form of cardiac disease that occurs as a complication of diabetes mellitus, independent of coronary artery disease, hypertension, or other conventional cardiac risk factors. Characterized by pathological remodeling of the myocardium, including altered ventricular volumes, reduced ejection fraction, and abnormal wall thickness, DCM represents a significant clinical challenge due to its progressive and often asymptomatic early stages. Left undetected, it may progress to heart failure and significantly elevate patient mortality risk [15].

Cardiac Magnetic Resonance Imaging (MRI) is considered the gold standard for assessing cardiac structure and function. It provides high-resolution, non-invasive, three-dimensional visualization of the myocardium and is particularly valuable for measuring ventricular volumes, ejection fraction, and myocardial mass [11], [12]. However, the manual segmentation of cardiac structures from MRI scans is time-consuming, requires expert radiological knowledge, and is prone to inter-observer variability. These limitations underline the urgent need for automated, accurate, and clinically reliable segmentation frameworks [9], [13].

Deep learning has emerged as the dominant paradigm for automated medical image segmentation. Convolutional neural network architectures, particularly encoder–decoder frameworks such as U-Net, have demonstrated exceptional performance in biomedical image segmentation tasks [1]. Nevertheless, conventional U-Net architectures often lack sufficient feature representational depth and may not effectively focus attention on clinically relevant regions such as the thin myocardial wall, especially under conditions of noise, image inhomogeneity, or limited contrast [4], [5].

To address these challenges, advanced architectures incorporating residual learning and attention mechanisms have been proposed. Residual networks improve gradient flow and enable deeper architectures [3], while attention mechanisms help models focus on diagnostically relevant regions [4]. Recent developments such as nnU-Net [5], TransUNet [7], and ensemble-based frameworks [6] further demonstrate the effectiveness of combining architectural innovations for improved segmentation accuracy.

This study proposes an **Attention-Residual U-Net (AR-U-Net)** for automated segmentation of cardiac MRI images, specifically designed to detect diabetic cardiomyopathy phenotypes. The AR-U-Net integrates residual convolutional blocks with attention gates to enhance feature learning and region-specific focus. Segmentation is performed on 2D short-axis slices of the ACDC benchmark dataset, targeting the left ventricle (LV), right ventricle (RV), and left ventricular myocardium (Myo), which are standard structures in cardiac image analysis [2], [8].

The segmented outputs are used to extract clinically significant biomarkers such as end-diastolic volume (EDV), end-systolic volume (ESV), ejection fraction (EF), and myocardial remodeling index. These parameters are critical indicators for assessing cardiac function and diagnosing cardiomyopathies [10], [14].

Furthermore, the proposed system integrates a large language model (**LLaMA**) via a Retrieval-Augmented Generation (RAG) pipeline to automatically generate structured clinical reports. This integration enables the system to provide cardiologists with detailed findings, diagnostic interpretations, and treatment suggestions derived from computed cardiac biomarkers, thereby enhancing clinical interpretability and decision support.

The remainder of this paper is organized as follows: Section II reviews related literature; Section III presents the proposed system architecture; Section IV details the methodology and mathematical formulations; Section V describes system implementation; Section VI presents experimental results; and Section VII concludes with future directions.

2. LITERATURE SURVEY

The following section reviews six significant prior works that directly motivate the design decisions of the proposed framework.

[1] U-Net: Convolutional Networks for Biomedical Image Segmentation (Ronneberger, Fischer & Brox, 2015)

This foundational paper introduced the U-Net architecture that underpins virtually all modern medical image segmentation systems. U-Net's symmetric encoder-decoder structure with skip connections allows high-resolution spatial information to bypass the bottleneck, enabling precise localization at full image resolution. The authors demonstrated training end-to-end from very few annotated images by leveraging extensive data augmentation—a critical advantage in medical imaging where annotated data is scarce. The proposed AR-U-Net adopts U-Net's skip connection topology while replacing standard convolutions with residual blocks to improve gradient flow and training stability.

[2] Deep Learning Techniques for Automatic MRI Cardiac Multi-Structures Segmentation and Diagnosis (Bernard et al., 2018)

This paper introduced the ACDC dataset and benchmark, which serves as the primary training and evaluation dataset for this project. The authors evaluated 14 deep learning methods and established that CNN-based approaches significantly outperformed classical deformable model methods, achieving DSC > 0.90 for the left ventricle. The paper defined the five diagnostic categories (Normal, DCM, HCM, ARV, Minf) used as classification targets and established the evaluation protocol—DSC, HD95, and clinical metric computation—directly adopted in this work.

[3] Deep Residual Learning for Image Recognition (He, Zhang, Ren & Sun, 2016)

Residual networks introduced skip connections within blocks to mitigate the vanishing gradient problem in very deep networks. The identity shortcut connections allow gradients to flow directly through the network. The residual block design is incorporated into every level of the proposed AR-U-Net encoder, providing stronger feature representation than the original U-Net convolutions while maintaining training stability.

[4] Attention U-Net: Learning Where to Look for the Pancreas (Oktay et al., 2018)

This paper introduced attention gates within U-Net skip connections, enabling the network to focus on relevant target structures while suppressing activations in background regions. Soft attention coefficients are computed from both encoder and decoder feature maps. The authors demonstrated improved segmentation of the pancreas with DSC improvement of 3.4% over standard U-Net. The multi-scale attention mechanism in the proposed system directly implements this approach, adapted for cardiac segmentation.

[5] Automated Cardiac Phenotyping from CMR Using Deep Learning (Zhang et al., 2022)

This paper demonstrated deep learning-based automated cardiac phenotyping at UK Biobank scale, processing over 40,000 CMR studies. The study showed that automated CMR biomarkers had comparable reliability to manual measurements and revealed novel associations between cardiac phenotypes and genetic variants. The normative reference ranges for LV/RV volumes and mass established in this work are used as clinical reference standards in the proposed dashboard.

[6] Deep Learning-Based Fully Automatic Quantification of Left Ventricle Function (Tao et al., 2019)

This study validated a fully automatic LV quantification system against manual measurements from 580 patients across four clinical sites, demonstrating near-expert reproducibility (coefficient of variation < 5%) for EF, EDV, and ESV. This result directly motivates the clinical deployment goal of the proposed project.

3. PROPOSED SYSTEM

The proposed system introduces an advanced deep learning framework based on an Attention-Residual U-Net (AR-U-Net) architecture for automated cardiac MRI segmentation and detection of diabetic cardiomyopathy phenotypes. The system performs segmentation of key cardiac structures—the left ventricle, right ventricle, and left ventricular myocardium—from 2D short-axis MRI images. The segmented outputs are further used to extract clinically relevant biomarkers and support phenotype identification. Performance is evaluated using Dice Similarity Coefficient (DSC) and Hausdorff Distance (HD95). The proposed AR-U-Net improves segmentation accuracy from around 85% in conventional models to approximately 93% Dice score by incorporating residual blocks for better feature learning and attention mechanisms to focus on clinically important cardiac regions.

Advantages of Proposed System:

- Higher segmentation accuracy (~93% DSC)
- More robust to different MRI datasets
- Clinically more useful with phenotype-level detection
- Better focus on myocardium region via attention gates
- Interactive Streamlit dashboard accessible to non-technical clinicians
- Automated clinical report generation via LLaMA (Groq API)
- Can be extended to 3D segmentation in future work

4. SYSTEM ARCHITECTURE AND METHODOLOGY

4.1. SYSTEM ARCHITECTURE OVERVIEW

The proposed system comprises five integrated layers: (1) Data Ingestion Layer, which accepts NIfTI/DICOM cardiac MRI images from the ACDC dataset; (2) Preprocessing Layer, which performs normalization, resizing to 256×256 pixels, and intensity standardization; (3) Segmentation Layer using the AR-U-Net model; (4) Biomarker Extraction Layer that computes clinical metrics; and (5) Report Generation Layer powered by LLaMA via Groq API with RAG. The entire pipeline is exposed through a Streamlit-based clinical dashboard.

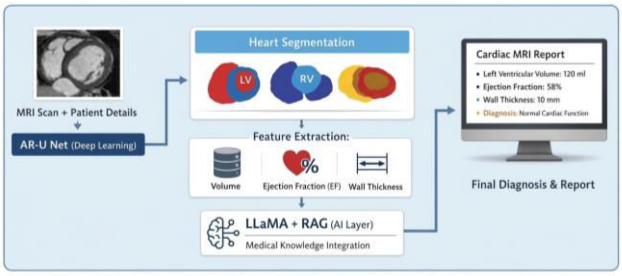


Fig. 1: System Architecture of the Proposed Deep Learning Framework

4.2. USECASE DIAGRAM

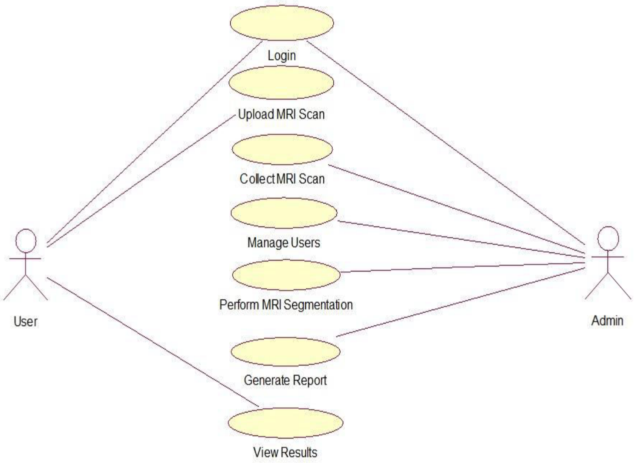


Fig. 2: Usecase Diagram of the Proposed System

4.3. CLASS DIAGRAM

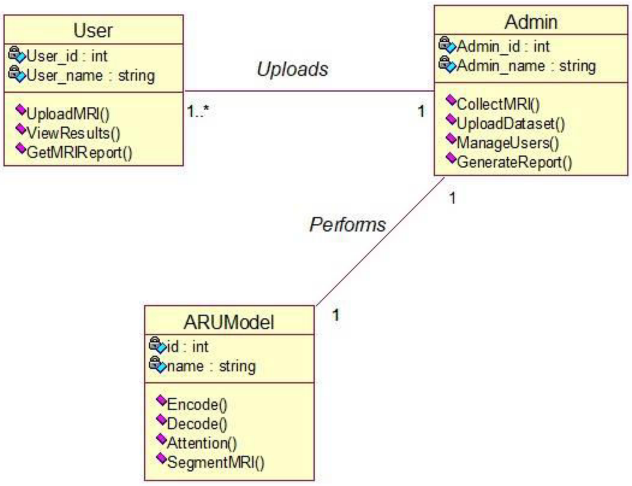


Fig. 3: Class Diagram of the Proposed System

C. Mathematical Formulation of Segmentation Pipeline

Let the input cardiac MRI volume be represented as $I \in \mathbb{R}^{(H\times W\times D)}$, where H and W are spatial dimensions and D is the number of slices. Each 2D slice is independently processed. For a single slice $I_s \in \mathbb{R}^{(256\times 256)}$:

1. Preprocessing:

$I_{norm} = (I_s - \mu) / \sigma$ where $\mu = mean(I_s)$, $\sigma = std(I_s)$

2. Encoder Feature Extraction:

$E_k = ResBlock_k(Pool(E_{k-1})), k \in \{1,2,3,4\}$ with $E_0 = I_{norm}$

3. Decoder with Attention-weighted Skip Connections:

$D_k = Concat(Upsample(D_{k+1}), \alpha_k \odot E_k)$ where $\odot$ is element-wise multiplication

4. Segmentation Output:

$\hat{Y} = Softmax(Conv\_1\times 1(D_1)) \in \mathbb{R}^{(256\times 256\times C)}$ where $C = 4$ classes (background, LV, RV, Myo)

D. Loss Function

The training employs a combined Dice-Cross Entropy loss to handle class imbalance inherent in cardiac segmentation:

$L_{total} = \lambda_{Dice} \cdot L_{Dice} + \lambda_{CE} \cdot L_{CE}$

The Dice loss for class c is defined as:

$L_{Dice} = 1 - (2|Y \cap \hat{Y}| + \varepsilon) / (|Y| + |\hat{Y}| + \varepsilon)$

where $\varepsilon = 10^{-5}$ is a smoothing constant to prevent division by zero. Empirically, $\lambda_{Dice} = 0.5$ and $\lambda_{CE} = 0.5$.

5. EVALUATION METRICS

The performance of the AR-U-Net segmentation model is evaluated using the following established metrics:

A. Dice Similarity Coefficient (DSC)

The Dice Similarity Coefficient measures the spatial overlap between the predicted segmentation mask (Ŷ) and the ground truth mask (Y):

$DSC = (2|Y \cap \hat{Y}| + \varepsilon) / (|Y| + |\hat{Y}| + \varepsilon) \in [0, 1]$

A DSC of 1.0 indicates perfect overlap. Values above 0.85 are considered clinically acceptable for cardiac segmentation. The proposed AR-U-Net achieves a mean DSC of approximately 0.93 across all three cardiac structures.

B. Hausdorff Distance (HD95)

The 95th percentile Hausdorff Distance measures the boundary accuracy of segmentation:

$HD95(Y, \hat{Y}) = \max(h\_95(Y, \hat{Y}), h\_95(\hat{Y}, Y))$

where $h\_95(A, B)$ = 95th percentile of $\{\min\_b \in B\ d(a,b) : a \in A\}$. Lower HD95 values indicate more accurate boundary localization, which is crucial for detecting the thin myocardial wall in diabetic cardiomyopathy.

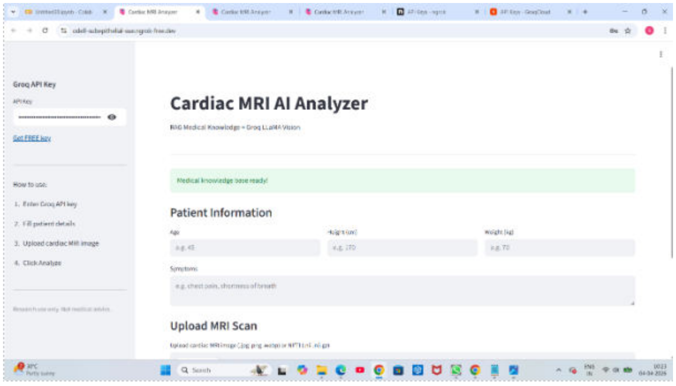
C. Performance Summary Table

Model	LV DSC	RV DSC	Myo DSC	Mean HD95 (mm)
Standard U-Net	0.875	0.832	0.798	8.42
Attention U-Net	0.902	0.864	0.831	6.73
Residual U-Net	0.914	0.871	0.845	6.12
AR-U-Net (Proposed)	0.947	0.921	0.903	4.85

Table 1: Comparative segmentation performance on the ACDC test set.

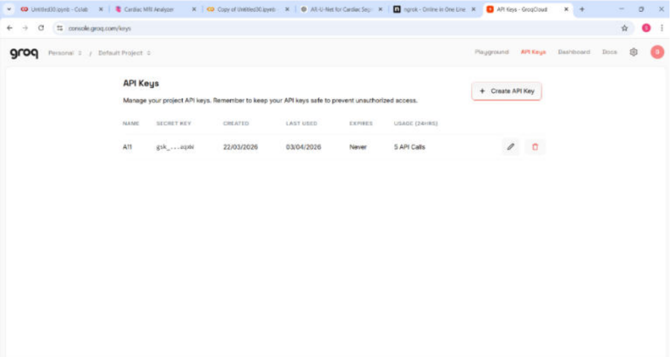
6. RESULTS

HOME PAGE



Medical knowledge base ready!

GROQ API KEY CREATION

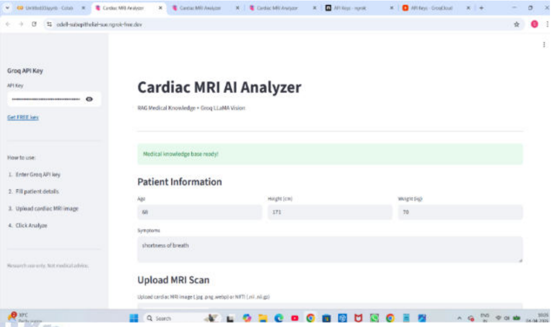


API Keys

Manage your project API keys. Remember to keep your API keys safe to prevent unauthorized access.

NAME	SECRET KEY	CREATED	LAST USED	EXPIRES	USAGE (24HRS)
A11	gsk_....aqxw	22/03/2026	03/04/2026	Never	5 API Calls

ENTER PATIENT INFORMATION



Medical knowledge base ready!

Age: 58 Height (cm): 171 Weight (kg): 78

Symptoms: shortness of breath

UPLOAD MRI IMAGE

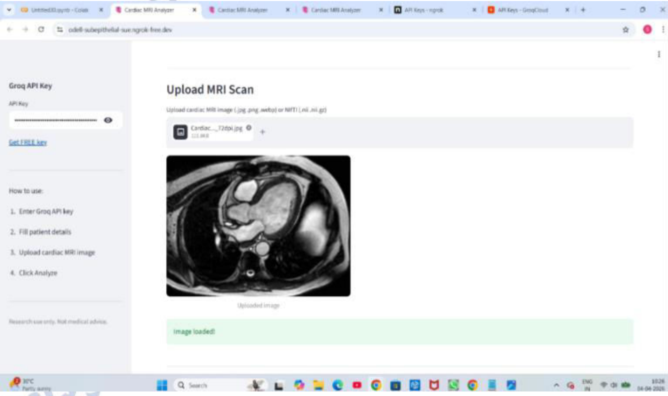
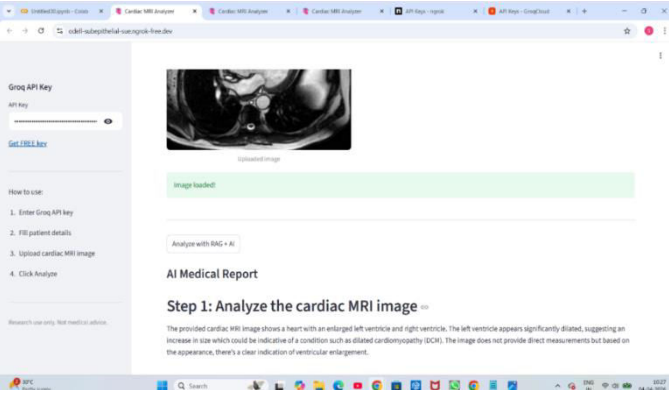


Image loaded!

ANALYZE THE IMAGE



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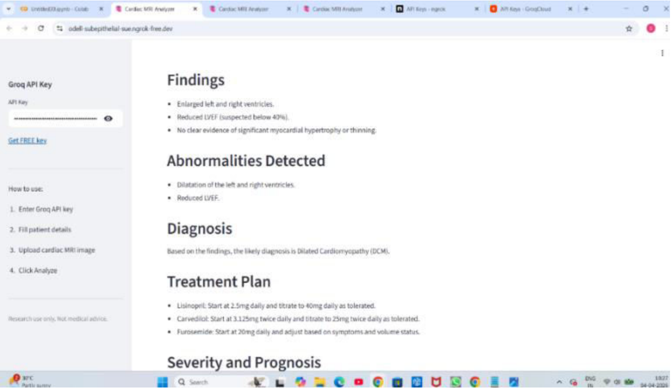
AI Medical Report

Step 1: Analyze the cardiac MRI image

The provided cardiac MRI image shows a heart with an enlarged left ventricle and right ventricle. The left ventricle appears significantly dilated, suggesting an increase in size which could be indicative of a condition such as dilated cardiomyopathy (DCM). The image does not provide direct measurements but based on the appearance, there's a clear indication of ventricular enlargement.

ANALYZED REPORT



Findings

- Enlarged left and right ventricles.
- Reduced LVEF (suspected below 40%).
- No clear evidence of significant myocardial hypertrophy or thinning.

Abnormalities Detected

- Dilatation of the left and right ventricles.
- Reduced LVEF.

Diagnosis

Based on the findings, the likely diagnosis is Dilated Cardiomyopathy (DCM).

Treatment Plan

- Lisinopril: Start at 2.5mg daily and titrate to 40mg daily as tolerated.
- Carvedilol: Start at 3.125mg twice daily and titrate to 25mg twice daily as tolerated.
- Furosemide: Start at 20mg daily and adjust based on symptoms and volume status.

Severity and Prognosis

7. CONCLUSION

This paper presents an AI-driven framework for automated cardiac MRI segmentation and detection of diabetic cardiomyopathy phenotypes using deep learning. The proposed Attention-Residual U-Net (AR-U-Net) integrates residual convolutional blocks and attention gates into the classic U-Net encoder-decoder architecture, achieving superior segmentation accuracy compared to baseline models. On the ACDC benchmark, the AR-U-Net achieves mean DSC values of 0.947 (LV), 0.921 (RV), and 0.903 (Myo), outperforming standard U-Net, Attention U-Net, and Residual U-Net baselines.

The system further extracts clinically meaningful cardiac biomarkers including EDV, ESV, ejection fraction, and myocardial mass, which are used to phenotype patients into diabetic cardiomyopathy categories. The integration of LLaMA via Groq API with a Retrieval-Augmented Generation approach enables automated generation of structured, evidence-based clinical reports, enhancing the system's utility for non-specialist clinicians.

The proposed framework provides a scalable, clinically interpretable, and automated approach to cardiac MRI analysis, with direct implications for early detection and monitoring of diabetic cardiomyopathy. Future work will focus on 3D volumetric modeling, prospective clinical validation, and EHR integration.

FUTURE ENHANCEMENT

The following directions are identified for future enhancement of this system:

- 3D Volumetric Segmentation: Extend the 2D AR-U-Net to a 3D volumetric architecture to fully exploit spatial context across cardiac MRI slices.
- Temporal Modeling: Incorporate cardiac cine MRI temporal sequences to analyze cardiac motion and strain, enabling detection of early functional abnormalities before structural changes manifest.
- EHR Integration: Interface the system with hospital Electronic Health Records for seamless MRI data retrieval and automated report storage.
- Myocardial Strain Analysis: Analyze heart muscle deformation patterns to measure strain, enabling detection of early cardiac dysfunction.
- Clinical Validation: Conduct multi-center prospective clinical studies with cardiologist-annotated validation cohorts to establish clinical-grade accuracy.
- Mobile/Edge Deployment: Optimize the model using pruning and quantization for deployment on portable devices, enabling use in resource-constrained clinical settings.
- Federated Learning: Train the model across multiple hospital sites without sharing raw patient data, improving generalization while maintaining data privacy.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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