



Left Ventricle Wall Thickness And Wall Motion Assessment Using Deep Learning.

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Abstract— The overall Assessment of the Left Ventricle's structural parameters like wall thickness and wall motion assessment are important steps for early diagnosis and effective treatment of any type of cardiac disorder or anomaly within. This project aims to develop a robust and efficient deep learning system for the automated assessment of the left ventricle (LV) wall thickness and wall motion using the cardiac MRI data. This project leverages the capabilities of deep learning techniques to analyse the cardiac MRI images. The model will be designed to extract important information about the total area of the LV and consequently wall thickness and wall motion using contours to mark the edges of the LV wall, allowing for a effective evaluation of cardiac health. By automating this process, healthcare providers can save time, reduce human error, and improve patient care. By automating this part of diagnosis in the process, this project can completely revolutionize cardiac care, making it more accessible, efficient, and precise. It can significantly impact the early detection and management of cardiovascular diseases, ultimately improving patient diagnosis outcomes.

Keywords— Left Ventricle, Cardiac MRI, Cardiac, Left Ventricular area, Segmentation, Deep Learning, Myocardial Infraction.

I. INTRODUCTION

In today's world different cardiovascular disorders and diseases make up the major fraction of morbidity and mortality across the world and especially in India. The evaluation of the anatomy and physiology of the left ventricle is critical in the range of cardiovascular diseases. Since the left ventricle is essential to the body's ability to pump oxygen-rich blood throughout the body, a precise assessment of it is necessary for the diagnosis and treatment of several cardiac disorders at an early stage.

In the past, medical imaging tests like echocardiograms and cardiac magnetic resonance imaging (MRI) have primarily relied on manual interpretation for the assessment of left ventricle wall thickness and wall motion. Even though it offers some insightful information, this process is not without its difficulties and errors. It frequently requires a significant amount of time and experience, which is prone to variation amongst healthcare professionals, and might not be easily accessible in environments with limited resources. Consequently, there has been increase in demand for better approaches to improve the effectiveness and precision of left ventricle evaluations.

Recent developments in artificial intelligence and its subfield of deep learning have demonstrated remarkable promise for transforming medical imaging analysis to a AI powered process. Deep learning algorithms are highly suited for image

recognition tasks because they can recognize intricate patterns and relationships within data, especially convolutional neural networks (CNNs) and recurrent neural networks (RNNs). By automating and standardizing the evaluation of left ventricle parameters, these techniques can be applied to cardiovascular diagnostics to provide a more effective and uniform method.

The methodology entails gathering and organizing a large dataset with multiple imaging modalities. The training of deep learning models will identify patterns suggestive of anomalies in the left ventricle. The assessment procedure will involve thorough testing in comparison to pre-existing manual assessments also. If this project is carried out successfully, it may cause a paradigm shift in cardiovascular diagnostics by providing a more effective, precise, and easily available way to measure the thickness and motion of the left ventricle wall. This in turn has the potential to greatly enhance both the general management of cardiovascular diseases and patient outcomes.

II. MOTIVATION

The motivation of this project is to implement deep learning methodology to evaluate the wall thickness and motion of the left ventricle using magnetic resonance imaging. The goal is to improve patient outcomes, facilitate early detection of cardiac abnormalities, and increase overall diagnostic efficiency.

III. RELATED WORK

Sulaiman Vesal et al proposed [1], which employs a deep learning methodology which makes the full quantification of left ventricle possible. The model uses the cine-MR images that are short axis based, which provides a three-dimensional morphological representation of the left ventricle. Here complete left ventricular quantification is the term used to describe a complete analysis and measurement of different parameters that show the overall health of the left ventricular chamber. Within the full left ventricular quantification, few of the important parameters that are particularly selected by the authors. The dataset used here was based on a 2018 SATCOM challenge training dataset. These images were further manually annotated to obtain the epicardium and endocardium which are the walls of the heart, and these annotations were also double checked with the healthcare professionals. The module uses a network architecture which in turn has two distinct stages. Stage one is segmentation stage where the MRI images are provided to it. In the second stage i.e. classification stage, the hard probabilities are fed to the multilevel CNN architecture. In this stage the encoder and decoder to extract the contours of the left ventricle and then produce the soft probabilities

which will be converted to hard probabilities. The Bland-Altman here was computed to about 95%. And being a light weight approach this model achieves remarkable feats such as being able to work with 580 images in approximately 2.2 seconds on a 4GB GPU memory which just shows the usability and feasibility of such a model.

Muhammad Ali Shoaib et al [2], Which presents a critical view of deep learning methods used for the left ventricle segmentation from very commonly used imaging techniques such as magnetic resonance images, echocardiography, and computer tomography. Here the author presents the emphasis on the magnetic resonance imaging as there is no other imaging methods that provide this level of anatomic information, and precision. Hence the MRI is often considered the reference standard for medical imaging. This study also demonstrates the use and importance of the network architecture especially convolutional neural networks (CNN) for the architecture implementation. Here we can observe the use of fully convolutional network (FCN) with both preprocessing and post processing of the dataset images and results. Here we use software, and hardware for training along with publicly available cardiac image datasets and self-prepared dataset also. The results of the segmentation can be evaluated using various well-known evaluation matrices such as the overlap-based DSC, and the spatial distance-based index like HD. But this proposed model architecture also faces some major hurdles like getting the already annotated images for the model. Also, the varying performance of the Deep Learning model based on the training dataset is another such problem faced here.

Xu S et al [3], proposes the use of ResUnet to classify the images as opposed to famous CNN counterparts such as the LeNet, AlexNet and also UNet. The dataset that is used here is provided by the MICCAI 2009 and LVQuan18 dataset which provides the short-axis cine MR images. The endocardium of the heart images are marked with cardiologist at both the end systole and the end diastole phases of the cardiac cycle. Here in the segmentation step of the proposed model the ROI are first cropped with the k-means and threshold adjustment methods. As the number of images to work with in this model is very less the author has employed the data augmentation method to increase the number of input images for the training dataset. Then the final preprocessed images from the segmentation stage goes to the ResUnet model where first a skip connection is used to highly improve the overall accuracy of the model and then a depth-wise separable convolution is also implemented for increased efficiency of the model.

Ebba Beller et al [4], voices the importance of ejection factor of the left ventricle which is a strong

parameter which can cause specific anomalies and disorders of the heart. Hence the accurate evaluation and examination of the ejection factor becomes very essential for the early detection and mitigation of any such irregularities. This paper proposes a novel deep-learning based approach to this problem which is adaptable to work on the CMR images in clinical settings to increase the overall performance of diagnosis process. Here fully automated analysis of LV volumes and function was performed using the model. The use of a deep learning-based algorithm allows for fully automated analysis of LV volumes and function. Automation leads to more consistent and reproducible results across different scans and healthcare providers. It is highly depended on the expert review received and the quality of the dataset that is received. The results were that about 20% of the data set were completely agreed upon and the remaining 80% had some minor corrections to them.

Michael V. Cohen et al[5], is a study that focuses on the implementation of a MRI tool with deep-learning methodology and use of convolutional neural networks (CNN) for the automatic segmentation of the LV. This study mainly focuses on the chemotherapy patients and are very susceptible to cardiotoxicity. Here a single-scan MRI method is proposed. In this the data is acquired through Displacement Encoding with Stimulated Echoes is an advanced magnetic resonance imaging (MRI) technique that provides detailed and quantitative information about myocardial motion for the full LV quantification. The working principle of DENSE MRI is that it is based on the encoding of tissue displacement information into the MRI signal. It uses specialized pulse sequences to encode displacement information directly into the acquired. Here the segmentation is performed using the DeepLabV3+ deep convoluted neural network. This method only focuses on the volumetric estimation of the LV chamber.

M.R. Avendi et al[6], There is a need for the automation of LV segmentation in today's world to effectively increase the diagnosis quality and also reduce the diagnosis time. While facing with automation of the LV chamber we can face some difficulties like varying brightness of the LV cavity due to different blood flow levels such as presence of papillary muscles. There are also some inherent noise present to the cine MRI images themselves. In this paper, the author proposes a fully automated process of segmentation of the left ventricle in cardiac MRI. Segmentation of the left ventricle (LV) from cardiac magnetic resonance imaging (MRI) datasets is an essential step for calculation of clinical indices such as ventricular volume and ejection fraction. In this work, the author employ deep learning algorithms combined with deformable models to achieve this task.



Table 1

SI.NO	TITLE	AUTHOR	MODEL/ALGORITHM	SHORT SUMMARY	ADVANTAGES	DISADVANTAGES
1	Spatio-temporal Multi-task Learning for Cardiac MRI Cleared out Ventricle Measurement	Sulaiman Vesal, Mingxuan Gu, Andreas Maier	ReLU, 3D CNN, DR-UNet	This uses an encoder-decoder network for segmentation of cardiac left ventricles. It utilizes a multi-task system to relapse LV records and classify the cardiac stage.	Quantification has demonstrated high prediction accuracy and robustness, despite varying degrees of cardiac morphology, image appearance, and low differentiate within the cardiac MR sequences.	Utilization of 3D spatio-temporal convolutions and multi-task learning might make the demonstrate computationally seriously and possibly challenging to execute and optimize.
2	Automated Echocardiographic Quantification of Ventricular Launch Division Cleared out using Deep Learning	Federico M. Asch, Victor Mor-Avi, David Rubenson, Samuel Surette	K-means clustering, Ejection fraction, Linear regression	The study tests a machine-learning algorithm for measuring left ventricular ejection fraction, but its use in point-of-care settings is constrained due to the trouble in getting particular sees	The utilization of a deep learning-based algorithm allows for fully automated analysis of LV volumes and function.	The precision of the automated algorithm is likely dependent on the quality of echocardiographic images.
3	Completely computerized evaluation of cleared out ventricular volumes and work in cardiac MRI: assessment of a profound deep learning-based algorithm	Ebba Beller, Anke Busse, Daniel Cantré	deep learning-based algorithm	The study investigates a deep learning algorithm's performance in automatically quantifying left ventricular volumes and function in cardiac MRI, using data from 50 patients.	The use of a deep learning-based algorithm allows for fully automated analysis of LV volumes and function.	The performance of deep learning algorithms can be highly dependent on the quality of the data used in training
4	A completely automated MRI-based left ventricular deformation analysis method based on deep learning semantic segmentation for cardiotoxicity	Michael V. Cohen, Samuel P. McQuiston, Christopher M. Malozzi	CNN and RNN algorithms	The study examines an automated tool using a deep convolutional neural arrange for quantifying left-ventricular strain gauges for identifying cardiotoxicity upon chemotherapy for breast cancer.	Automation reduces the potential for human error and inter-operator variability	The performance of deep learning algorithms can be highly dependent on the quality and representativeness of the training data.

5	Using Deep-Learning Algorithms to Simultaneously Identify Right and Left Ventricular Dysfunction From the Electrocardiogram	Akhil Vaid, Kipp Johnson, Atul Kukar	Deep learning algorithms	The study aims to develop deep learning models for quantifying ventricular dysfunction from ECG data, enhancing diagnostic workflow.	Developing DL tools for assessing ventricular function from ECG data can be cost-effective compared to other imaging modalities like echocardiography	The quality of ECG data, as well as the natural language processing (NLP) extraction of information from echocardiogram reports, can vary
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IV. METHODOLOGY

In this section we first lay out the objectives that we intend to achieve and then we will introduce the proposed methodology to achieve these objectives.

A. Objectives

The objective of this work is to upgrade the productivity and accuracy of evaluating important cardiac parameters by utilizing cutting-edge computational techniques. The main goal is to create a solid DL model that will measure the left ventricular area and then consequently wall thickness and wall motion precisely in imaging tests like cardiac MRIs and echocardiograms. To ensure the model's adaptability to different patient demographics and imaging conditions, it must be trained on a diverse dataset. Moreover, the project aims to enhance the DL model's capacity to evaluate the left ventricle's wall motion. The system attempts to analyse dynamic changes in the wall motion by incorporating complex algorithms, offering important insights into cardiac function and potential abnormalities. The ultimate objective is to develop an efficient tool that will help medical professionals in the diagnosis of cardiovascular conditions by providing a detailed evaluation of the left ventricle's motion patterns in addition to an accurate quantification of wall thickness. The project also highlights how crucial reliability and interpretability are in clinical settings. In order to do this, the deep learning model will be assessed by human experts and validated against current standards. The project aims to support the development of a clinically applicable tool for routine cardiac assessments by guaranteeing the reliability and accuracy of the model. This could potentially improve the speed of diagnosis in cardiovascular medicine. All things considered, the project fills a significant gap in the medical field by fusing deep learning technology with cardiac imaging to provide a more thorough and effective method of left ventricle assessment.

B. Dataset

I obtain cardiac MRI data from [8]. This is a dataset which is custom where the raw dataset was marked by makesense.ai. In order to use Makesense.ai to process a dataset, first you must upload your data—whether it consists of text, audio, images, or other kinds of information that require annotation or labeling—to the platform. Make use of Makesense.ai's annotation tools to label and annotate your data. This is an important step in helping ML models learn to identify patterns. Use the platform's validation tools to review and confirm the annotations' correctness and quality after they have been annotated. After you're satisfied, export the annotated dataset in an XML or JSON format

which works best with your machine learning framework. Use this labeled data to train, test, and validate your models by integrating it into your machine learning workflow. Remember that creating a machine learning model is frequently an iterative process. In order to use Roboflow for machine learning data splitting, first you must upload your image dataset to the platform. To improve your dataset, label and preprocess features using Roboflow's annotation tools. After annotation, export the dataset in a format that is widely used, such as YOLO or COCO, to make sure it works with popular machine learning frameworks. Although Roboflow lacks a feature for splitting data, you can manually divide your dataset into test, validation, and training sets as per the needs of your project. After splitting the datasets, use the validation set to fine-tune hyperparameters, the test set to assess model performance on unknown data, and the training set to train models. The datasets can then be seamlessly integrated into your ML workflow.

A well-liked and efficient algorithm that detects the objects called You Only Look Once has been widely applied in a variety of computer vision applications. YOLO is especially well-known for its real-time processing powers, which allow it to locate and identify objects in pictures or video frames very quickly. Using a single pass through the neural network, the algorithm divides or segregates the input image into a grid and predicts bounding boxes (outlines) and class probabilities for each grid cell, enabling the simultaneous detection of multiple objects. YOLO is useful in situations where speed and efficiency are critical, like in object recognition systems, autonomous cars, and surveillance. It is adaptable for a wide variety of applications because it can manage several object classes on a single network.

C. Architecture

Firstly, we use a predetermined model for image analysis and feature extraction processes on the cardiac MRI dataset. YOLOv5, is used for object detection algorithm designed for real-time applications. It divides an image into a grid or pixel and predicts bounding boxes or end points and class probabilities for objects within each grid cell. YOLOv5 has gained popularity because of its speed and accuracy. While it is not mainly designed for segmentation, but it can be adapted for tasks like left ventricle segmentation. In this context, this model can be trained on a dataset of echocardiographic images annotated with bounding boxes around the left ventricle. The trained model can then predict bounding boxes for the left ventricle in unseen images. Post-processing techniques, such as extracting the region within the bounding boxes, can be applied to achieve segmentation. While the

model may not provide pixel-level segmentation, its object detection capabilities can serve as a fast and efficient means for identifying and localizing the left ventricle in medical images, providing a valuable tool for cardiac image analysis.

Post-processing steps are essential for calculating the area of the LV which is identified in the pre-processing. The bounding box coordinates obtained from models predictions serve as the basis for extracting the ROI from the original image. Once the ROI is isolated, potential preprocessing steps, such as resizing or normalization, can be applied. Subsequently, the area of the LV within the

ROI is calculated using appropriate geometric formulas, considering the shape characteristics of the LV. This may involve straightforward methods, such as computing the area of an ellipse if the LV appears elliptical, or more sophisticated techniques like contour-based area calculations for irregular shapes. The computed left ventricle area can then be integrated with other results from the project, such as assessments of wall thickness and motion. Validation against ground truth data and expert input is crucial to ensure the accuracy and clinical relevance of the calculated left ventricle area, allowing for adjustments and refinements as needed.

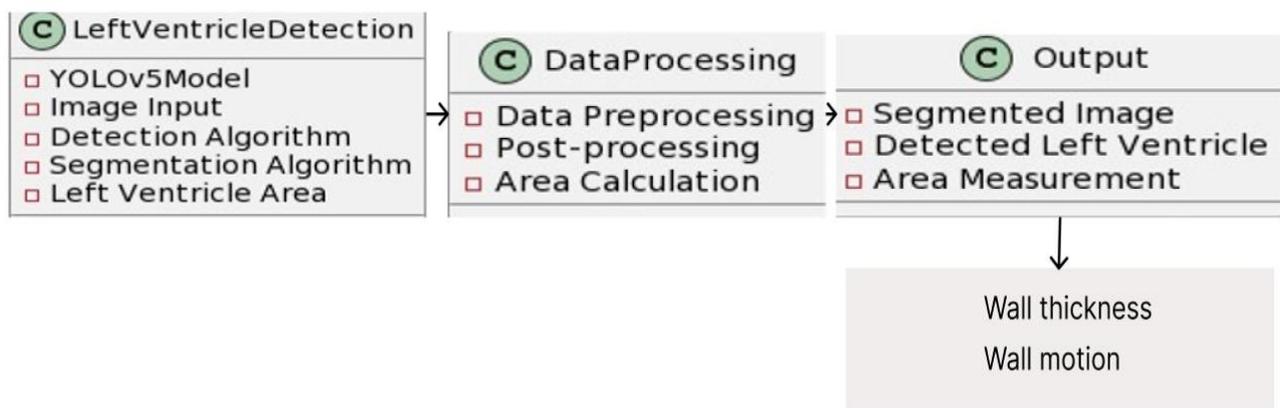


Fig (1). Representation of the workflow of the deep learning model



Fig (2). Image representing the short-axis view of the LV section.
Left ventricle under rest.



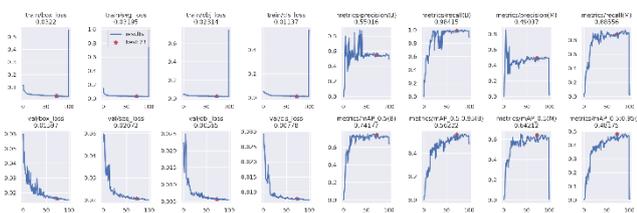
Fig (3). Image representing successful marking

We utilize an image segmentation algorithm, such as a CNN, to identify the boundaries of the LV in the short-axis images. Train the model on annotated data to accurately segment the region of interest. After the LV has been segmented, locate the boundary points by using contour detection techniques. Common techniques include contour finding functions found in image processing libraries or edge detection algorithms such as Canny edge detectors. Then we use post-processing

techniques to smooth out irregularities and guarantee a more accurate depiction of the LV boundary in the detected contours. For this, methods like filtering or morphological operations can be used. detected contours. For this, methods like filtering or morphological operations can be used. Determine the wall thickness by calculating the separation between the left ventricle's inner and outer contours. Geometric algorithms or the calculation of the separation between

corresponding points on the contours can be used to accomplish this measurement. The LV boundaries and wall thickness can then be seen visually by superimposing the contour outlines on the original short-axis images.

V. RESULTS



In our project, we developed a novel model for assessing the left ventricle wall thickness based on the area measurements of the left ventricle. The model employs a mapping technique to correlate these measurements accurately. Here are the key findings: The model achieved an impressive recall of 0.98415, indicating its effectiveness in including accuracy, sensitivity, specificity, will be satisfactory. Visualizations of our model's predictions versus ground truth further highlight its proficiency in capturing complex patterns and subtle variations. Moreover, our approach will

identifying true positive cases (i.e., correctly detecting left ventricle wall thickness) during box drawing. However, the precision during box drawing was 0.55016, suggesting room for improvement in minimizing false positives. The overall recall rate, considering the entire left ventricle assessment process, stands at 0.88556, while the precision for the complete assessment is 0.49037. Our findings underscore the potential clinical utility of this approach and pave the way for more accurate and efficient left ventricle assessments.

VI. CONCLUSION

In our project we present compelling results that showcase the effectiveness of our novel approach. Our deep learning model, trained on a diverse dataset, will demonstrate high accuracy and precision in assessing left ventricle wall thickness and wall motion. The quantitative metrics,

show promising generalization across different patient demographics and clinical scenarios, indicating its robustness in real-world applications. This ultimately results in an effective and quick diagnostic process.

VII. REFERENCES

- [1] Sulaiman Vesal, Mingxuan Gu et al "Spatio-temporal Multi-task Learning for Cardiac MRI Cleared out Ventricle Measurement" IEEE Journal.
- [2] Raza Ali, Khairunnisa Hasikin, Azira Khalil, Yan Chai Hum, Yee Kai Tee, Samiappan Dhanalakshmi, "An Understanding of Deep Learning Methods for Left Ventricle Segmentation", *Computational Intelligence and Neuroscience*, vol. 2023, Article ID 4208231, 26 pages, 2023. <https://doi.org/10.1155/2023/4208231>
- [3] Xu S, Lu H, Cheng S, Pei C. "LV Segmentation in Cardiac MRI via an Improved ResUnet. *Int J Biomed Imaging*." 2022 Jul 8;2022:8669305. doi: 10.1155/2022/8669305. PMID: 35846793; PMCID: PMC9286995.
- [4] Ebba Beller, Anke Busse, Daniel Cantré, "Completely computerized evaluation of cleared out ventricular volumes and work in cardiac MRI: assessment of a profound deep learning-based algorithm".
- [5] Michael V. Cohen, Samuel P. McQuiston, Christopher M. Malozzi, "A completely automated MRI-based left ventricular deformation analysis method based on deep learning semantic segmentation for cardiotoxicity".
- [6] M.R. Avendi, Arash Kheradvar, Hamid Jafarkhani, "Using Deep-Learning Algorithms to Simultaneously Identify Right and Left Ventricular Dysfunction From the Electrocardiogram".
- [7] Karen G Grajewski, Jadranka Stojanovska, El-Sayed H Ibrahim, Mohamed Sayyoub, Anil Attili, "Left Ventricular Hypertrophy: Evaluation with Cardiac MRI".
- [8] <https://github.com/MIrohith/lvdataset> - custom dataset of MRI image.

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