# Segmentation of Heart Wall Muscles and Detection of Hypertrophic Cardiomyopathy from 2D Echo Images Using U-Nets

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***Abstract*—In this paper, we focus on the development of an automatic technique to obtain the segmentation of the heart wall in ultrasound images using U-Nets. The detection of hypertrophic cardiomyopathy (HCM) and similar conditions is achieved by measuring the thickness of the posterior heart wall in the left ventricle. We measure the thickness of the segmented heart wall using repeated morphological operations in the form of erosion to give us an idea of its real thickness. Medical literature suggests that if the thickness of the heart wall is greater than 15mm, then we classify the image as a potential case of HCM. In our experiment, we have taken $139$ images in our training, and $34$ images in our test set in order to examine the accuracy of our technique. We find that the U-Net obtains an accuracy of $0.85$ in terms of the Dice similarity coefficient.**

***Index Terms*—HCM, U-Net, ROI, LVH, Segmentation**

## I. Introduction

Hypertrophic cardiomyopathy is a disease in which the walls of the heart become thickened or enlarged. According to a genetic study, mutations in 14 genes code for sarcomere proteins [17], which are declared the primary cause of HCM and affect the functioning of cardiac muscle contractions. Symptoms of HCM include shortness of breath in young athletes, arrhythmias, lack of energy, and sudden cardiac arrest. HCM can be asymptomatic to some extent, and several other diseases also show similar symptoms to HCM, making it difficult to identify the HCM pattern during diagnosis. The most common and critical form of HCM compared to other conditions is HCM of the left ventricle.

Different methods, such as echocardiography [15] (heart ultrasound scans), cardiac MRI, and electrocardiogram (ECG) [14], are used by experts to analyze the performance of the heart. Echocardiography is an ultrasound technique that uses high-pitched sound waves transmitted through a transducer. The echoes received by different parts are turned into moving pictures in a sequence of images with less information, which may introduce some vulnerability. Consequently, cardiologists spend more time predicting and making decisions. Cardiac MRI is a costly method as it utilizes cardiovascular magnetic resonance (CMR) imaging to provide functional and morphological information about the heart for the evaluation, management, and diagnosis of patients with suspected cardiovascular disease. Electrocardiogram (ECG) is another examination that records the electrical activities of the heart to predict and monitor different abnormal heart conditions. However, ECG is a less sensitive tool and cannot accurately predict HCM. Several HCM phenotypes, such as asymmetric septal hypertrophy (ASH), apical hypertrophy, concentric hypertrophy, mid-ventricular obstruction, and non-obstructive HCM, can be used to classify HCM.

Diagnosis of HCM is typically done using echocardiography and cardiac MRI. The usual technique to detect HCM is to have a radiologist examine the ultrasound/MRI sequences and determine if the person has HCM based on an expert's opinion. However, it is a fact that multiple raters do not consistently rate the presence of HCM and its localization in the same way (inter-rater variability). Additionally, the raters may not segment the images the same way on different days (intra-rater variability) [16]. Therefore, there is a need to detect and track HCM in a timely and consistent manner, and as such, automatic techniques to segment the heart wall and detect the presence of HCM are greatly desirable.

Given this need, it is unsurprising to note that several attempts have been made to automatically detect the presence of HCM. The studies performed in the field of Hypertrophic Cardiomyopathy (HCM) have led to the development of various methods for the automatic detection of HCM and its phenotypes [4]. Existing methods of deep learning-based HCM prediction include the Watershed Segmentation algorithm [1], which is used to locate the

Region of Interest (ROI) for automatic segmentation of heart wall abnormalities by comparing two apical four-chamber 2D echo videos. In 2022, Adam Budai and others [2] discovered the automatic detection of HCM from Cardiac MRI using 3D-ResNet. This method detects left ventricular hypertrophic regions. If any symptoms or patterns of HCM are observed during the MRI procedure, this method changes the CMR protocol to detect the HCM ROI. ResNet is a complex architecture with 150 layers of convolution and max-pooling. This architecture overcomes the vanishing gradient problem that occurred during the training of the dataset with its skip connection feature. A study conducted by J. Jenifa Sharon and Dr. L. Jani Anbarasi [3] used Fuzzy C-means Clustering for segmentation, and HCM was classified based on the features extracted from the echo images, such as kurtosis, entropy, histogram, etc., applied to a classifier. Disease classification was executed using Levenberg-Marquardt with backpropagation, which provided good results in this technique. The Multitask cascaded convolutional neural network (MTC-Net) [6] is another deep learning-based algorithm developed for HCM prediction to segment the left ventricular myocardial muscles from echo images. The thickness is computed using the Euclidean distance transform. The ground truth, which is the borders of the left ventricle region marked by doctors, is compared with the obtained segmented borders of MTC-Net for prediction. Studies convey that to predict left ventricular hypertrophy or HCM, the thickness of the heart walls must be greater than or equal to 15mm. A cohort study [7] was performed to locate and segment the left ventricular endocardial regions of the heart using echocardiography. The segmented regions are used to calculate the ejection fraction and evaluate the regional wall motions. The proposed work discusses the automatic segmentation of the left ventricular endocardial region using U-Net. U-Net ResNet 34 [8] architecture is used with two-chamber and four-chamber views of the heart and the cardiac structures of the left region of the heart. The model is developed using U-Net architecture with residual blocks that extract the boundaries of the left ventricular endocardium, left ventricular epicardium, and Left atrium. The performance of the developed model using U-Net ResNet 34 shows better results in extracting the boundaries. The segmentation of boundaries of the heart from an echocardiogram depends on several features, such as low contrast heart tissue, speckle noise, the structure of the image, left ventricular papillary muscles, and other physiological characteristics of the heart. The developed classifier classifies each pixel individually into four classes: the background, the area bounded by the LV endocardium, the area bounded between the corners of epicardium and endocardium of LV, and the area bounded by the corners of LA. The predictions are performed by concatenating the high-level features from U-Net ResNet 34 and U-Net ResNet 50. The use of residual blocks resolves fading gradients, selects weights more accurately, and provides better segmentation results. A local directional pattern (LDP) and pre-trained ResNet 50 are used [10] to locate the hypertrophic regions in the ultrasound scans. The study is conducted using apical four-chamber views of the heart. Indexing [11] is the method used for classification based on the threshold greater than or equal to 15mm, indicating the presence of HCM. However, none of them take full advantage of the contextual features that U-Nets can and further, these techniques depend on the entire sequence, and do not detect HCM from a single ultrasound image frame. In order to fix these deficiencies, we have, in this paper, focussed on a U-Net based technique to detect and segment the HCM region from a single ultrasound frame.

Echocardiography provides several advantages in the evaluation of cardiac controls. It is non-invasive and cost-effective compared to other imaging techniques. It contributes detailed information about wall thickness, heart chamber sizes, blood flow patterns, and valve function. It permits the identification of different cardiac abnormalities. The limitations of echocardiography rely on the operator's experience to obtain accurate and precise measurements [15]. Furthermore, certain patient factors, such as lung disease or obesity, can limit the acoustic window and affect image quality. The proposed method develops a simple, cheap, and consistent automatic tool [13] to analyze echo images using an U-Net-based architecture model to segment the heart wall muscles from the 2D echo images. For the classification of HCM and normal heart wall muscles, the thickness of the segmented heart walls was evaluated using morphological erosion. The thickness of the heart wall muscles is computed by the number of erosions to completely erode the interventricular septum and left ventricular posterior walls of segmented heart wall muscles and pixel resolution to obtain a threshold point for classification. The number of erosions required for an HCM heart is greater than that of a normal Heart.

This paper is organised as follows: In section 2, we define the data and other material we employ. In section 3, we describe the technique of the U-Net. In section 4, we present our results, both qualitative and quantitative. In section 5, we conclude with a discussion of our results and present our conclusions.

## II. Materials and Methods

The goal of this research is to develop an algorithm for hypertrophic cardiomyopathy classification from Echo images. The ultrasound scans contain parasternal long axis views. Our dataset was collected from the images provided by the department of cardiology of Amrita Institute of Medical Sciences (AIMS). The AIMS data set had 173 ultrasound images, containing both HCM, and normal control subjects. All the ultrasound data sets, had segmentation provided by one expert for the region of the heart wall for each of the images. An example of the ultrasound image and its corresponding heart wall region used as dataset has been shown in Fig. 1.

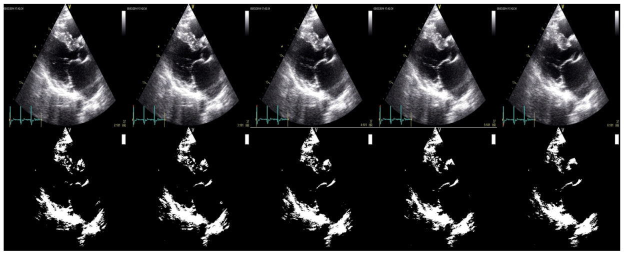

Fig. 1. Input Image and Corresponding mask

## III. Model Architecture

The U-Net architecture was first introduced by Olaf Ronneberger, Philipp Fischer, and Thomas Brox in 2015 [9] and used for medical image analysis. Fig.2 shows the model of UNet Architecture. The U-Net architecture consists of two main components: the contracting path (encoder) and the expanding path (decoder). These paths are symmetrical and connected by skip connections, ensuring information flow between corresponding layers. In the contracting path (encoder), the input image is processed through convolutional layers to extract high-level features. Each convolutional layer is followed by a rectified linear unit (ReLU) activation function and max pooling, reducing the spatial dimensions. The expanding path (decoder) takes the feature maps from the contracting path and performs up-sampling to recover the original spatial resolution. In each decoding step, the up-sampled features are concatenated with the corresponding feature maps from the contracting path. The concatenated features then pass through a series of convolutional layers to refine the segmentation output. Skip connections play a crucial role in the U-Net architecture by allowing direct information flow between the contracting and expanding paths. These connections concatenate feature maps with the same spatial resolution, preserving fine-grained details and spatial information during up-sampling, which contributes to accurate segmentation. The final output of the U-Net architecture is a pixel-wise segmentation map with the same dimensions as the input image. Generally, a small, final convolutional layer is used to map the high-dimensional features to the desired number of classes or channels. The activation function in the final layer depends on the specific task, such as

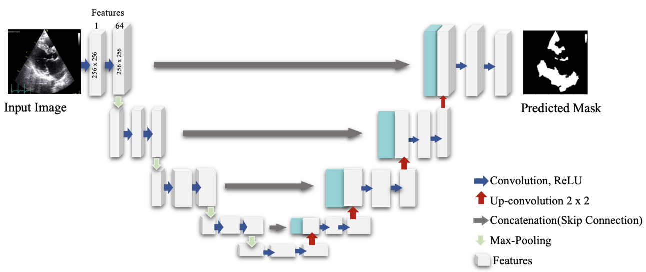


Fig. 2. U-Net Architecture

sigmoid for binary segmentation or SoftMax for multi-class segmentation. The U-Net architecture's [12] ability to capture both local and global contextual information, combined with the skip connections, makes it highly effective in accurately segmenting objects and regions in images. To create the UNet model aimed at segmenting the left ventricular posterior wall, a series of convolutional layers are utilized. The initial portion of the model consists of a contraction path where the first block contains two 3x3 convolutional layers, each having 16 filters. Following these layers, a ReLU activation function is applied along with the same padding. Subsequently, a dropout layer with a rate of 0.1 is added after the first convolutional layer, and a max pooling operation with a pool size of 2x2 is performed. The contraction path is further enhanced by incorporating three additional convolutional layers, resulting in a total of four convolutional blocks. At each level, the number of filters doubles. The expansive path of the model commences with the first block that employs a transpose convolutional layer featuring 128 filters, a kernel size of 2x2, and a stride of 2x2. The output from this layer is then concatenated with the corresponding layer from the contraction path. Two more convolutional layers, utilizing 3x3 filters and 128 filters each, along with a ReLU activation function and the same padding, are subsequently applied. A dropout layer is employed after the first convolutional layer in this block. This pattern is repeated for four expansive paths, incorporating the concatenation of corresponding layers from the contraction path and applying convolutional layers. Once the UNet model is constructed, it is compiled using the Adam optimizer as the chosen optimization algorithm for training. The learning rate parameter is set to 1e-3, which corresponds to a learning rate of 0.001. The optimizer is responsible for adjusting the model's weights based on the computed gradients to minimize the loss during the training process. The binary cross-entropy loss function is selected for this particular model, as it is suitable for binary classification tasks where the output represents a probability between 0 and 1. This loss function measures the dissimilarity between the predicted probability distribution and the true binary labels. Considering the U-Net model's binary segmentation task, the chosen loss function is appropriate. The model's performance is evaluated using the accuracy metric.

The U-Net provides the segmentation of the heart wall from the ultrasound images. We, now, need to measure the thickness of the heart wall in order to determine whether a person has HCM or not.

### A. Morphological Erosion

Morphological erosion [5], a digital image processing technique used to gradually erode or remove the boundaries of objects in an image. This process involves applying a small shape or pattern, known as a structuring element, to the image. The structuring element scans the image pixel by pixel, and if all the corresponding pixels in the structuring element match the image pixels, the center pixel of the structuring element is retained. Otherwise, it is eroded or eliminated. By performing morphological erosion, the boundaries of objects are effectively reduced or made smaller. It eliminates the external or outermost layer of pixels around the object boundaries. This operation is beneficial for tasks such as noise reduction, separating connected objects, or altering the shape and size of objects. Morphological erosion is commonly used with binary or gray scale images, where pixel values represent object presence or intensity. The degree of erosion depends on the size and shape of the structuring element. Smaller structuring elements result in more pronounced erosion, while larger ones preserve more of the original shape. To achieve specific image processing objectives, morphological erosion is often followed by other operations like dilation, opening, or closing. It is a valuable tool in various applications such as image segmentation, feature extraction, and noise reduction.

### B. Training Scheme

The dataset consist of 173 HCM echo images and normal heart echo images. The training was performed over the HCM based echo images for applying the morphological operation to compute the thickness of the heart walls muscles focused on Inter ventricular Septum and left ventricular posterior walls. The dataset was split into three parts: training (80%), and testing (20%). In the context of the U-Net architecture, input images and their corresponding pixel-wise segmentation masks are used to develop the Segmentation model to extract the cardiac wall muscles from the echo images. It is an effective architecture for image segmentation tasks, where the goal is to classify each pixel in an image into specific categories.

To train a U-Net model, a dataset of labelled training samples is needed. Each sample consists of an input image and a corresponding segmentation mask. The input image is the raw image, while the segmentation mask is a binary image of the same size, with labels assigned to each pixel. Human annotators manually label the regions of interest in the input images, creating the ground truth segmentation masks. During training, the U-Net model takes an input image and produces a predicted segmentation mask. The predicted mask is compared to the ground truth mask, and the model's parameters are adjusted using back propagation and gradient descent to minimize the difference between them. This iterative process continues until the model achieves satisfactory performance. By training the U-Net model on a large dataset of annotated training samples, it learns to accurately segment objects or regions in new images. The architecture's contracting and expanding paths enable it to capture both local and global contextual information, making it highly effective for image segmentation tasks, even with limited data samples. Morphological Erosion operation is practiced on the segmented cardiac wall muscles to measure the thickness. Thickness is evaluated by Summing the number of erosions required to erode the Left ventricular Posterior wall regions. For the classification of HCM heart and Normal Heart, the Number of erosions required to erode the Left ventricular Posterior wall regions will be greater for HCM heart echo images compared to the Number of erosions required to erode the Left ventricular Posterior wall regions of Normal heart. Fig.3 shows the steps involved in the classification of HCM and Normal Heart.

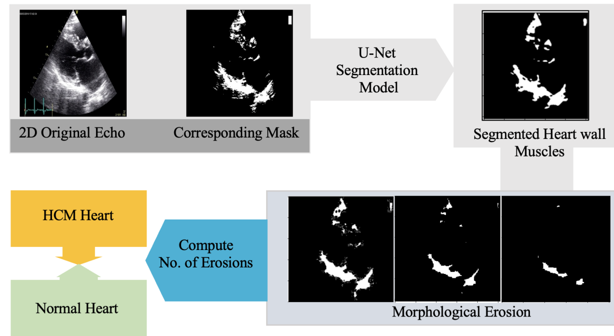


Fig. 3. Workflow

### C. Human Evaluation

The algorithm's performance was assessed by comparing it to human experts in a realistic evaluation setup that simulated everyday examination procedures. The human experts were given echo images of 173 subjects and a brief patient history without explicit reference to the actual disease. The images included a full echo scan, specifically the parasternal long axis views. The analysis focused on echo images from both the normal and hypertrophic cardiomyopathy (HCM) groups. The experts observed that in the HCM condition, the thickness of the Interventricular Septum and Left Ventricular Posterior wall reduced the size of the Left ventricular Cavity.

## IV. Result

By conducting experimental analysis, demonstrates that the algorithm outlined in Section 2 can achieve similar performance to human experts. Fig.4 shows the accuracy and loss plots of the model developed using U-Net.

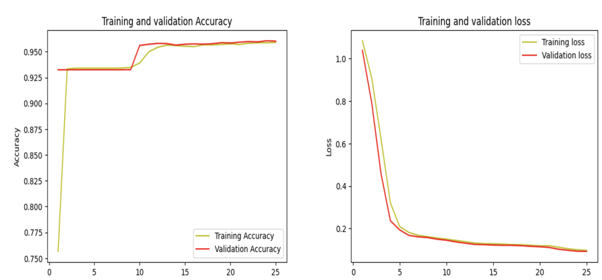


Fig. 4. Accuracy and Loss Curve to Analyse the Model

The model achieves an accuracy of 80% when computed using the dice similarity coefficient to segment the LV posterior cardiac wall muscles from echo images. This evaluation was performed on 173 echo images related to hypertrophic cardiomyopathy (HCM). Fig.5 shows the predicted model for the input image and its corresponding pixel wise mask for segmenting the cardiac wall muscles from echo images using

U-Net Architecture. The Segmented model obtained were analyzed from a human point of view and using objective and quantitative analysis. Qualitatively, the observations were accurate and precise when compared to other segmentation algorithms. Quantitatively, the overall performance was computed using parameters like accuracy, precision, sensitivity, specificity, recall and Dice similarity coefficient.

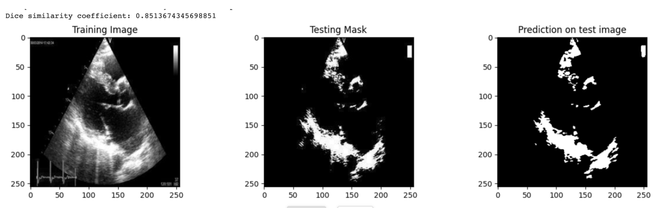


Fig. 5. Predicted Model using U-Net Architecture for Segmentation

Morphological erosion was applied considering the pixel dimensions of the segmented model [5]. For instance, assuming each pixel represents 1mm, the number of erosions required to erode or break the regions of the Interventricular septum or Left ventricular posterior wall was determined as 15. This results in a thickness of 15mm, which is used to classify the image as HCM. Additionally, if the number of erosions required to erode the Interventricular septum is greater than the number needed for the Left ventricular posterior wall, it indicates the presence of Asymmetric Hypertrophy.

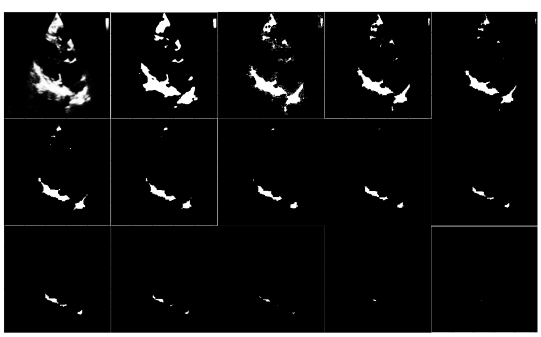

Fig. 6. Erosion on Left Ventricular Posterior walls

Fig.6 shows the Number of erosions performed to erode LV posterior wall of the U-Net Segmented cardiac wall predicted model from echo images.

The code employs the Dice similarity coefficient technique to assess the similarity between the predicted mask image and the ground truth mask image. This method quantifies the alignment between the two masks, indicating how well the predicted mask corresponds to the ground truth. The dataset from Amrita Institute of Medical Sciences (AIMS) with 173 images were utilized for left ventricular posterior wall segmentation from echo images, employing the U-Net Architecture. The overall Dice similarity coefficient for the test images is determined to be 0.84.

## V. Discussion and Conclusions

The U-Net architecture, for image localization and medical image segmentation, enables pixel-by-pixel predictions in the image. The network exhibits robust predictive capabilities even when working with limited datasets, primarily due to the extensive implementation of data augmentation techniques. In this proposed method, the primary objective was to segment heart wall muscles from echo images for hypertrophic cardiomyopathy detection. For this purpose, the U-Net segmentation algorithm was employed and found to be more accurate and precise when compared to other segmentation algorithms, even when using a limited dataset. The developed model based on the U-Net Architecture provides segmented heart walls. Additionally, morphological erosion was performed on the left ventricular posterior region of the segmented cardiac wall muscles to measure the thickness of the LV posterior wall. In terms of classification, a greater number of erosions were conducted on HCM echo images compared to normal hearts. Moving forward, future work entails comparing the thickness of segmented heart walls with that of normal heart walls using morphological erosion to predict whether the heart is normal or exhibits HCM. Moreover, there is a focus on differentiating between different types of HCM and HCM phenotypes.

## VI. Abbrevations

HCM - Hypertrophic Cardiomyopathy
LVH - Left Ventricular Hypertrophy
ROI - Region of Interest
MRI - Magnetic Resonance Imaging
LV - Left Ventricle
LA - Left Atrium
IVS - Inter Ventricular Septum
PSNR- Peak Signal to Noise Ratio
SSIM - structural index similarity

## VII. Acknowledgement


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