

## Abnormality in Mitral Leaflets Mobility Detection Using Deep Learning

**Vishal Chandra**, Computing and information science, Usha Martin University, India  
vcvishalchandra@gmail.com

**Prattay Guha Sarkar**, Cardiology, RIMS, India  
prattay\_2904@yahoo.com

**Vinay Singh**, Computing and information science, Usha Martin University, India  
vinaysinghuma@gmail.com

### Abstract

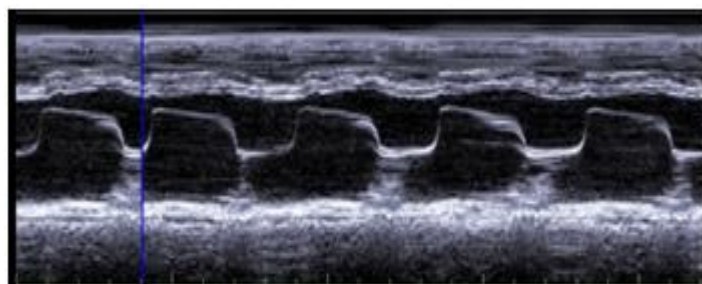
RHD (Rheumatic heart disease) is still a burden in underdeveloped countries. It affects the heart's wall and valves, mainly the mitral valve. TTE (Transthoracic Echocardiography) is a non-invasive technique used to look inside the heart, including the heart valve and valve's motion. RHD leads Mitral stenosis. Guidelines for assessing the mitral valve based upon the mitral valve's morphology include leaflets' mobility, leaflets' thickness, and sub valvular thickness. Sonographers able to track the mitral leaflets' motion using the M-mode of mitral valve (MV) in the long-axis view. In this research, we used an M-mode echocardiography view for the mitral valve's leaflet's motion. This research used the deep learning technique for detection abnormality in the mitral leaflets' movement automatically. Mitral stenosis restricts the mitral leaflets' motion. Our proposed deep learning (DL) model achieved the testing accuracy of 96% having f1 score of 96% on the testing dataset of 64 patients. Our training dataset is of 320 people. Even smaller dataset proposed model gives a promising result. In a normal mitral valve, leaflets flip two times during diastole (mid diastole). else ways, in the Rheumatic mitral valve, there will minimal forward movement. So, there is a distinguishable pattern between normal, and RHD affected mitral valve can see.

### Keywords:

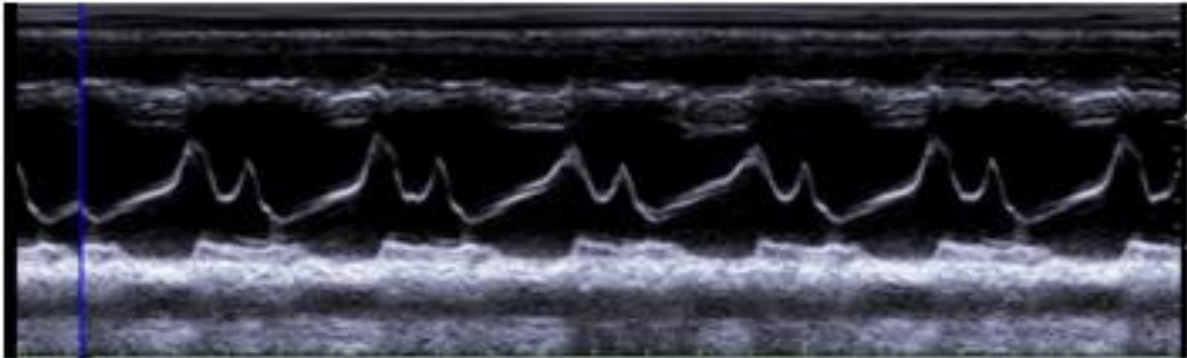
CNN, m-mode, mobility, mitral leaflets.

### 1. INTRODUCTION

The M-mode is the chosen imaging technique in the initial periods of ultrasound. The M-mode is described as the ultrasound wave's time-motion display along a selected ultrasound line. The M-mode benefit is its high sampling rate, resulting in a higher resolution such that it is possible to capture, view, and quantify even very fast movements. The downside is that the ultrasound line is connected to the tip of the ultrasound region. The M-mode perpendicular to the structures shown (i.e., the septum), which is difficult to align, contributes to incorrect measurements. Through reconstructing the M-mode from the 2D picture (post-processing), the anatomical M-mode circumvents this constraint. The anatomical M-mode permits the cursor line to be placed freely. The time resolution, though, is considerably less than that of the traditional M-mode.



**Figure 1 normal mitral leaflets motion**

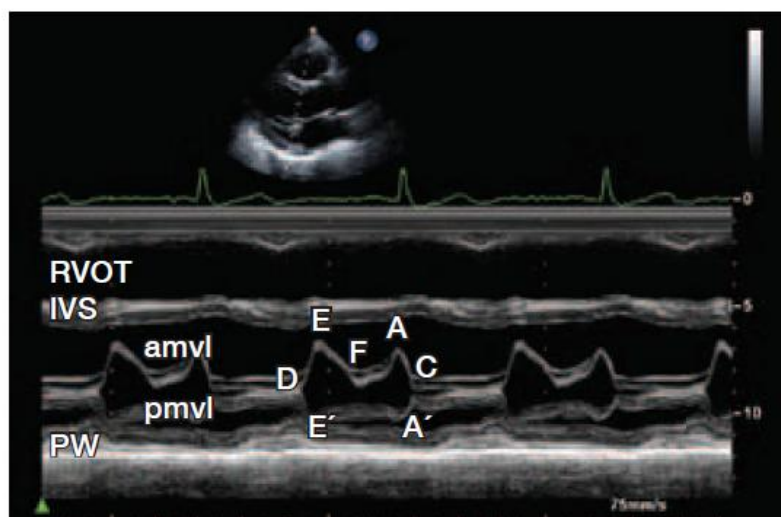


**Figure 2 reduced mobile mitral leaflets motion**

Mitral valve is a gateway between the ventricle and left atrium. Its leaflets control and regulate blood flow in systole and diastole. It should completely close during the systole mitral valve so that no reverse flow of blood to the left atrium. During diastole, it should open entirely so that blood fills the left ventricle. In a normal mitral valve, its leaflets do two times forward movements.

On the other hand, RHD mitral valve has few or no minimal forward motion during diastole, preventing blood flow from left atrium to the left ventricle. Figures 1 and 2 are images of normal mitral leaflets movement and restricted forward movement. one can quickly notice a wave shape in both pictures, but in normal has two peaks. The affected valve has no peak round or flat shape. Two peaks due to due to two-time flip in diastole.

Before the invention of 2d echo or 3d echo, M-mode echocardiography was used to assess mitral valve. EF slope is a crucial factor in this Method. It is high in normal mitral valve and ever few or sometimes zero in echo images. EF slope is the slope of the first peak. Figure table1 shows a description of the structure of the mitral leaflets.



**Figure 3. illustration of the structure of mitral valve in m-mode**

**Table 1. anterior mitral leaflet points**

Points	Description
D Point	<ul style="list-style-type: none"> <li>marks position of the mitral valve leaflets at the onset of diastole</li> </ul>
E Point	<ul style="list-style-type: none"> <li>reflects the maximal opening point of the mitral leaflet due to the early, rapid filling phase of diastole</li> <li>early, rapid filling and opening of the mitral valve occurs when the pressure in the LV falls below the pressure in the LA</li> </ul>
F Point	<ul style="list-style-type: none"> <li>the most posterior position of the leaflet immediately following the E point</li> <li>posterior motion occurs when the pressure difference between the LA and LV decreases as the LV pressure rises as the LV fills and as the LA pressure falls as the LA empties</li> </ul>
E-F slope	<ul style="list-style-type: none"> <li>represents the initial diastolic closing motion of the anterior leaflet</li> <li>this slope is an indicator of the rate of LA emptying and/or LV filling</li> <li>normally, LA emptying and LV filling is rapid resulting in a steep E-F slope</li> </ul>
A point	<ul style="list-style-type: none"> <li>reflects the point of leaflet 're-opening' that occurs following atrial contraction</li> <li>with atrial contraction the LA pressure increases resulting in another bolus of blood being ejected into the LV</li> </ul>
B Point	<ul style="list-style-type: none"> <li>refers to the position of the anterior leaflet at the onset of ventricular systole</li> <li>this point is usually absent when there are normal LV filling pressures</li> </ul>
C point	<ul style="list-style-type: none"> <li>denotes the final position of leaflet closure immediately prior to ventricular systole</li> </ul>

## 2.LITERATURE REVIEW

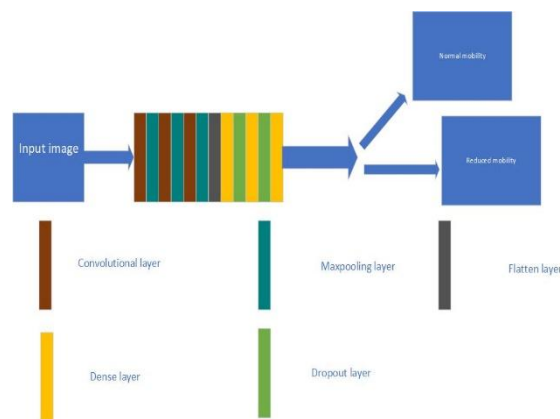
A literature review can readily available by papers [1] and [2]. They have included articles till 2018; our review is till 2020 in Echocardiography. Echocardiography Uses rays of ultrasound to visualize the heart's internal structure, which is an imaging modality. Deep learning applications for Echocardiography consist of classification, detection, segmentation, report generation, and tracking. Most of the contributions by using deep learning (DL) are segmentation and detection. The most successful and popular deep learning algorithms (models) for segmentation is Unet[3] and its variants, DBNs. In [4], the authors proposed a DBN method that is much robust than the previous level set and deformable techniques for visualization for left ventricle visualization. Nascimento et al. [5] proposed a manifold learning method that divides the image into patches such that each patch offers left ventricle segmentation. After merging the patches' output image, using the DBN classifier where each patch has assigned a weight, this technique makes it a more robust output with a small dataset. In [6], the authors compare regularized FCN with simple FCN demonstrate better results.. Use of DL for echocardiographic viewpoint classification. Madani et al. [7] proposed a deep learning model for the classification of 15 different echocardiography views; they used a CNN having a six-layer and achieved better results than echocardiographers. In [6], for the left ventricle ejection fraction classification, the authors proposed a 3D residual CNN network using TTE(Transthoracic Echocardiography) images. In [8], the authors proposed a deep learning (DL)algorithm for the real-time echo quality scoring Lowering the variability of operators during the echocardiography process. They used recurrent layers to utilize the consecutive information in the echo loop. Perrin et al. [9] classify congenital heart disease; in this study, authors trained AlexNet with 59151 echo frames between five pediatric populations. Moradi et al. [10] proposed a method based upon VGGnet and doc2vec [11] technique to produce semantic descriptors for echo images. Their model identified 91% of disease instances and 77 % of valve disease severity. For establishing the relationship between echocardiography images and medical records, Moradi et al. [12] proposed a deep learning model. Chen et al. [13] proposed a model capable of left ventricle segmenting in 5 different 2D views (apical, 2, 3, 4, and 5-chamber

vista. The second was extended in Carneiro and Nascimento [14] for tracking of left ventricle. for segmentation mitral leaflets Costa et al. [14] used Unet by training with 30 videos. Kusunose et al.; compared various image classification models to classify regional wall motion abnormalities [15]. Leclerc et al. [16] used large open datasets for left ventricle segmentation. Dehghan et al. [17] used Unet for the detection of anomalies by multi-view regression. Moradi [18] used a modified Unet for left ventricle segmentation better than any previous method. Hanif bin et al. [19] proposed a way for the detection of the aortic valve. Omar used CNN for the classification of wall motion abnormality. Smistad used a convolutional neural network for real-time view classification in TTE. Smistad et al. [20] used a modified Unet for LV segmentation. Dong et al. [21] proposed combined traditional techniques with CNN for left ventricle segmentation. Studies are also covered with direct disease classification by analyzing echocardiography images.

### 3. Data Collection, Annotation

cosy care hospital provided echocardiography data, Ranchi, Jharkhand, India, including subjects, under informed consent. A total of 100 clips have been taken from 100 different subjects with ages from 16 to 65. A total of 140 images for normal and 140 for rheumatic affected mitral valve were used for training, and 28 for normal, 28 rheumatics for testing purpose testing, annotated by an echocardiographer with expertise.

### 4. Proposed work



**Figure 4 proposed model.**

Our proposed model is very simple consists of three deep convolutional units, three max-pooling layers, and a flatten layer, three dense layers, and two dropout layers. The convolutional units are used for feature extraction; on the other hand. Dense layers help classify. 256X256 image size used in this study. Dropout 0.5 remove 50% of neurons for avoiding overfitting. In the convolutional unit, 32 filters were used.

First convolutional layer- filters=32, kernel size=3,3

Maxpooling layer- (2,2)

Second convolutional layer – filter=64, kernel size=3,3

Third convolutional layer- filters=128, kernel size=3,3

First dense layer -512 neurons

Dropout 0.5 (50 percent)

Second dense layer -256 neurons

Third dense layer (classification layer) -1 neuron

The activation function for convolutional layers is "relu."

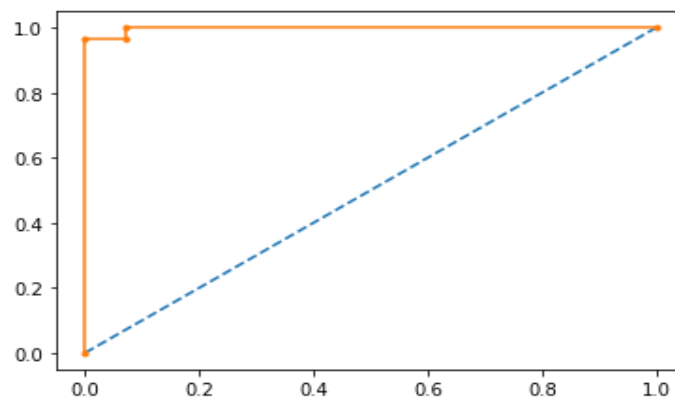
The activation function of the classification layer is "sigmoid."

## 5. Results

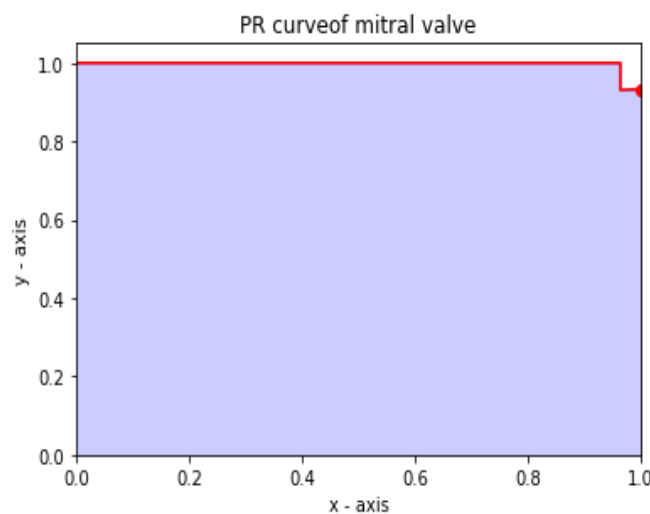
As far as results are concerned, our proposed models achieved 98 percent accuracy, having an f1 score of 98. We tested our proposed model with 56 having 28 in each class (mobile and reduced mobility). classification report is given below

	Precision	recall	f1-score	support
normal mobility	0.96	0.96	0.96	28
reduced mobility	0.96	0.96	0.96	28
accuracy			0.96	56
macro avg	0.96	0.96	0.96	56
weighted avg	0.96	0.96	0.96	56

AUC and PR curves are shown in Figures 5 and 6.



**Figure 5 AUC**



**Figure 6 PR curve**

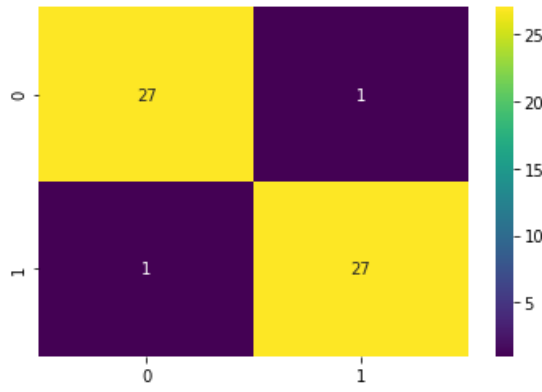


Figure 7 confusion matrix

### 6. Output images from testing

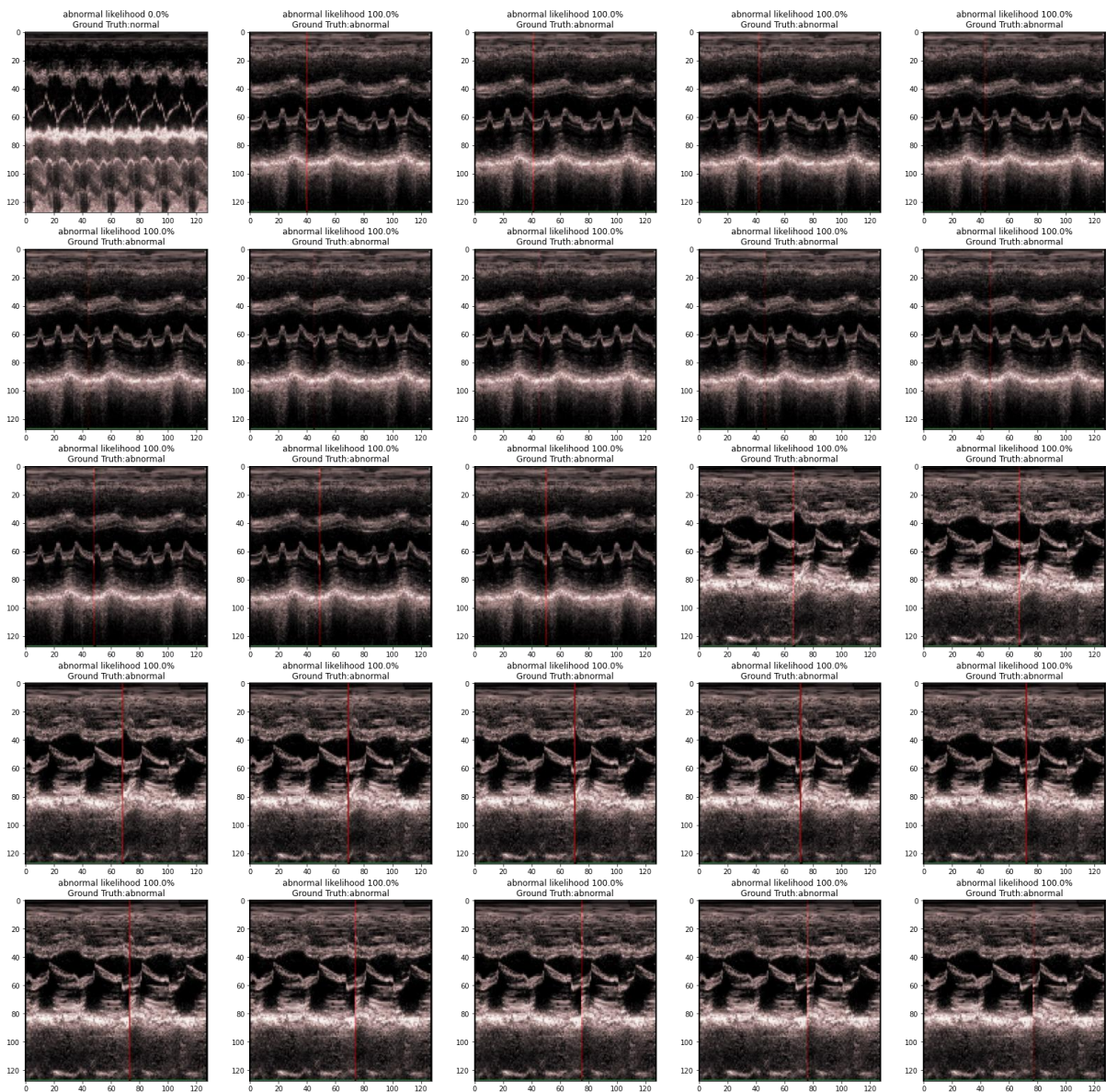
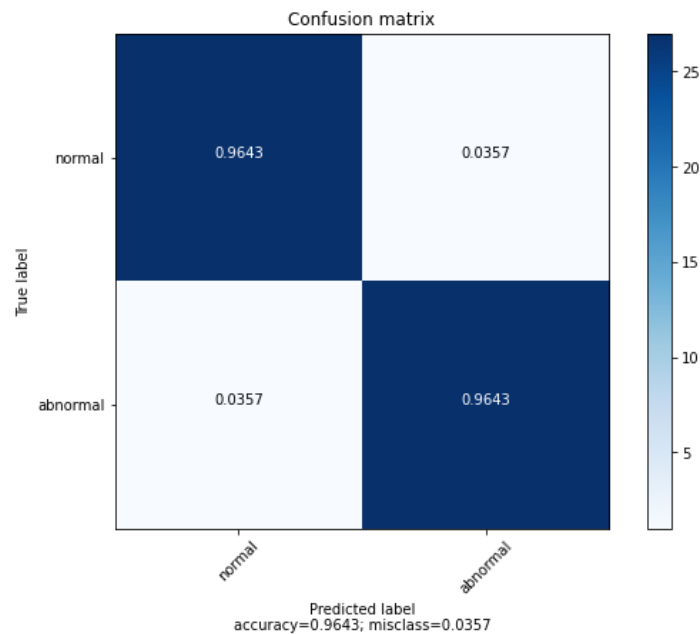


Figure 8 testing image output



From the confusion matrix, it can observe only two value has misclassified. From the PR and AUC curve, we compare the value with their images, respectively. Figure 8 contains images having out from proposed models. Figure 9 is a normalized confusion matrix with misclassification 0.0179.

## 7. Conclusion and future scope

Detection of reduced mobility of mitral leaflets is successfully classified and predict our proposed model with an accuracy of 98%. Our proposed model has classified normal mitral valve and rheumatic mitral valve leaflets. This means we successfully classified mitral valve between normal mitral valve and mitral stenosis affected valve. For the future, if the dataset is large, one can classify mitral stenosis as severe, moderate, and mild. Even a small dataset model gives good results

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