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# Mitral stenosis detection using Deep Learning technique in PSAX view TTE

**Vishal Chandra, PrattayGuha Sarkar, Vinay Singh**
Research Scholar, Research Scholar, vcvishalchandra@gmal.com
Assistant Professor, RIMS,Ranchi, prattay_2904@yahoo.com
Associate Professor, UMU, Ranchi, vinaysinghuma@gmail.com

**Abstract**: The goal of this research is to identify abnormality automatically in the mitral valve,stenosis, or normal in parasternal short-axis view (PSAX).one of the common and widely spread valvular diseases is mitral valve disease. It is still a burden in underdeveloped countries, for health sociality as well as countries. Mitral valve approximately 80 percent of valvular diseases. According tothe World Heart Foundation Guidelines, based on mitral leaflets morphology. The mitral valve areacan calculate using the PSAX view. In mitral stenosis mitral valve has a specific shape, which is similar to a fish mouth. Our main goal is to detect this abnormality so that sonographers investigate further better.Our evaluation metrics have concern f1 score for normal is 99%, and mitral stenosis is 99%, and accuracy is 99 percent. The dataset we for training is 900 and testing 600 for testing purposes: confusion matrix, ROC curve, PR curve measured for our evaluation result. We created the MobileNet inspired model to solve the classification of normal or mitral stenosis valve.Our proposed model only detectsan abnormality in the mitral valve in the PSAX view. It reduces the time of Echocardiography.We aim to use a minimum number of parameters to solve this problem to make real-time analysis possible.

**Keywords**: CNN, deep learning, Echocardiography, mitral stenosis, PSAX, MobileNet.

1. **Introduction**: in cardiovascular diseases, mitral valve diseases are common, and in 99 percent of cases,Rheumatic Heart Disease is responsible (RHD). It deforms mitral leaflets, mainly the tip of leaflets, and rheumatic fever is responsible for RHD. Autoimmune response to group A streptococcal pharyngitis bacterial infection does all infections, which affect heart valves. Although eradicated in developed countries due to modern antibiotics and hygiene food, it is still a significant burden in underdeveloped countries and developing countries. Three significant diseases happen due to RHD Mitral stenosis (MS), mitralregurgitation (MR), and mixed lesions.We can calculate the mitral valve area from Echocardiography, which is highly operator dependent in the PSAX view. We use the same view PSAX view to detect abnormality in the mitral valve. Echocardiography can easily see or diagnose RHD, especially mitral stenosis and Mitral Regurgitation. If there is an abnormality, then the mitral valve area should calculate; otherwise,there is no need to calculate MVA(mitral valve area). In the previous 25 years, it spread all over the globe.


Fig 1.a abnormal mitral orifice

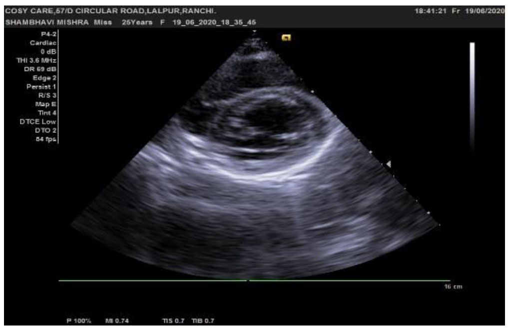


Fig 1.b normal mitral orifice.

From the above figure, we can say that thereis some abnormality in the abnormal mitral orifice. In developed and under-developing countries, the number of patients to the doctor is essential; if the rate is high, the cardiologist has enough time to serve the patient. Still, there is a low ratio; thus,a cardiologist has very few times to investigate the disease. This study aims to reduce the burden from sonographers toanalyzequickly and efficiently; our proposed model only detectsan

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abnormality; if an exceptionis observed, the go for further investigation; otherwise, the patient has no mitral stenosis. Estimating the mitral valve using planimetry is highly operator dependent and difficult. This method saves time and effort for sonographers. We also used a minimum number of parameters to solve this problem to run on mobile devices smoothly. Compared to ResNet50, inceptionV3, MobileNet, DenseNet121, all are capable of solving the problem. Still, they have large numbers of parameters, so we obtained the same accuracy with minimum numbers of the parameter means minimum computation by our proposed model. The proposed model consists of depthwise convolutional layers and regular convolutional layers.

2. **Literature review**:Echocardiography uses ultrasound waves to visualize the heart's internal structure, 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 are segmentation and detection. The most popular deep learning model is Unet[1] and its variants, DBNs. In [2], the authors proposed a DBN method that models the left ventricle's visualization showing, more robust than previous level sets and deformable techniques. Nascimento et al. [3] proposed manifold learning that divides the data into patches that each patch offers segmentation of the left ventricle. The output imageis obtained by merging patches by a DBN classifier in which each patch has assigned a weight. In this way, it produces a more robust output with a limited number of data set. In [4], the authors used a regularized FCN compared with simple FCN and demonstrated better results. Use of Deep learning for echocardiographic viewpoint classification. Madani et al. [5] used a CNN with a six-layer to classify 15 views (12 videos and three still) of TTE and achieved better results than echocardiographers. In [6], the authors proposed a 3D residual CNN network to classify ejection fraction classification using TTE images. In [7], the authors proposed a system for real-time echo quality scoring for getting feedback to reduce operator variability duringthe echocardiography process. They used recurrent layers to utilize the consecutive information in the echo loop. Perrin et al. [8] trained AlexNet with 59151 echo frames to classify congenital heart disease between five pediatric populations. Moradi et al. [9] proposed a method based upon VGGnet and doc2vec [10] technique to produce semantic descriptors for echo images. Their model identified 91% of disease instances and 77 % of valve disease severity. Moradi et al. [11] proposed a deep learning model for establishing the relationship between echocardiography images and medical records. Chen et al. [12] proposed a model capable of segmenting the left ventricle 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 the left ventricle. Costa et al. [10] used Unet for segmentation mitral leaflets by training with 30 videos. Kusunoseet al.; compared various image classification models to classify regional wall motion abnormalities [11]. Leclerc et al. [13] used large open datasets for the segmentation of the left ventricle. Dehghan et al. [14] used Unet for the detection of anomalies by multi-view regression. Moradi [15] used a modified Unet for left ventricle segmentation better than any previous method. Hanif bin et al. [16] proposed a way for the detection of the aortic valve. Omar used CNN for the classification of wall motionabnormality. Smistad used a convolutional neural network for real-time view classification in TTE. Smistad et al. [17] used a modified Unet for LV segmentation. Dong et al. [18] 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 and Annotation**cosy care hospital provided echocardiography data, Ranchi, Jharkhand, India, under informed consent of all subjects. A total of 100clipshave taken from 100 different issues with age from 16-65 years. Total of 3000 images obtained from 100clips, 2400 is used for training, and600 for testing annotated.

**4. Proposed pipeline**

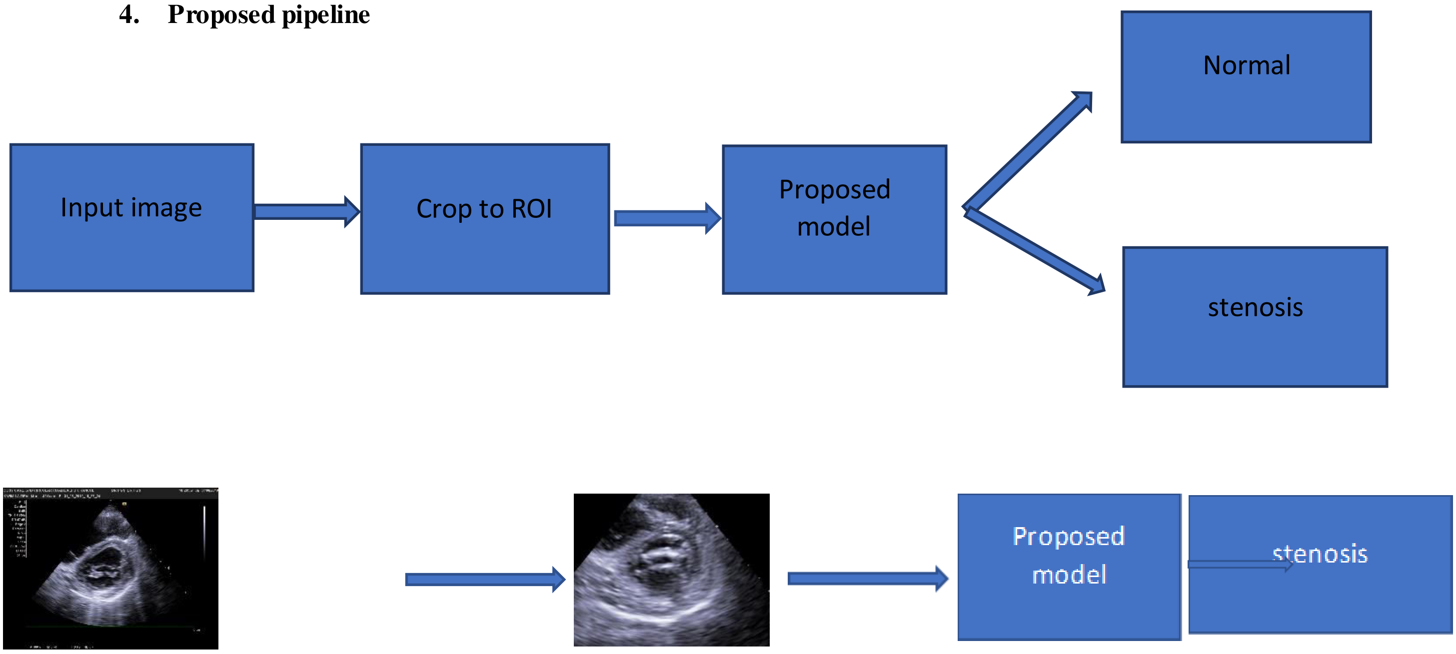


Fig 2. Proposed pipeline.

There are two stages in the proposed pipeline"crop to ROI (region of interest)" and second pass it to the proposed model to predict normal or stenosis. The input image is the parasternal short-axis view (PSAX). We used modified yolo2 with the MobileNet back-end approach for mitral orifice detection or boundaries around its model to crop.

5. **Proposed model**: the proposed model has been used to classify mitral stenosis or normal mitral orifice. The proposed model has one unit as follows:
   1. Depthwise convolutional layers(2D)
   2. Batchnormalization
   3. Pointwise convolutional layer(2D)
   4. Batchnormalization
   5. Activation function(relu)

Depthwise separable convolutional layer

Batchnormalization

Pointwise convolutional layer

Activation function

Sigmoid

GlobalAveragePooling

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Convolution layer (2D)

Dropout (0.50)

Dense layer


Fig 3 proposed model

- **Depthwise convolution** performs spatial convolution independently on each channel of input.
- **Pointwise convolution**, 1x1 convolution, projecting the channel's output by the depthwise convolution onto a new channel space.

  Difference between Inception module and separable convolutions:
- Separable convolutions perform first channel-wise spatial convolution and then perform 1x1 convolution, whereas Inception performs the 1x1 convolution first.

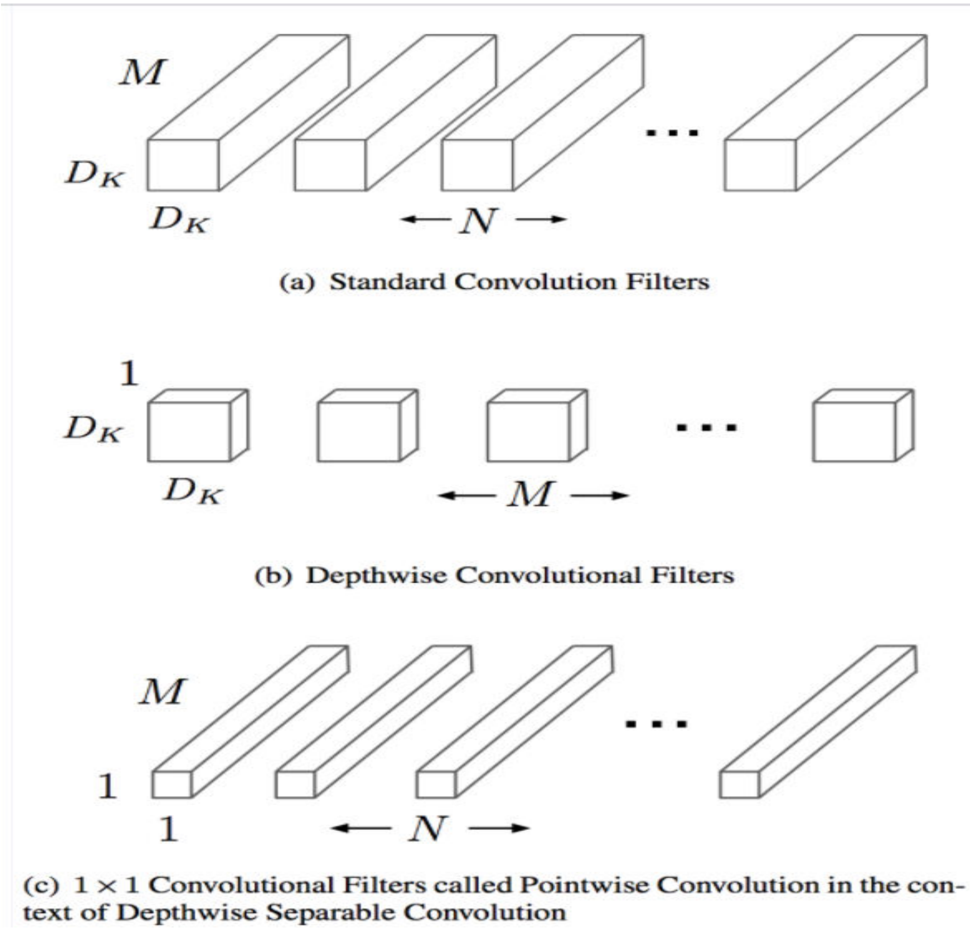


Fig 4. a, b, c Depthwise, and pointwise convolutional layers

We used filters of 32 ,32,64,128,128,256, image size = (256,256,3) value of alpha is 1. We used padding is the same. We also used stride in depthwise convolutional layers (3,3), and a pointwise convolutional layer is (1,1).

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Total numbers of the parameter are 137409, the batch size chosen four due to hardware limitation, we use Nvidia GTX 1050 Ti of 4Gb graphics card, with an i9 processor and 8 Gb of RAM.

**6. Results**our classification report as follows

| | Precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 1.00 | 0.98 | 0.99 | 300 |
| 1 | 0.98 | 1.00 | 0.99 | 300 |
| accuracy | | | 0.99 | 600 |
| macro avg | 0.99 | 0.99 | 0.99 | 600 |
| weighted avg | 0.99 | 0.99 | 0.99 | 600 |

We used 600 samples for testing purposes and got 99 percent accuracy. Here 0 represents normal, and 1 illustrates stenosis.

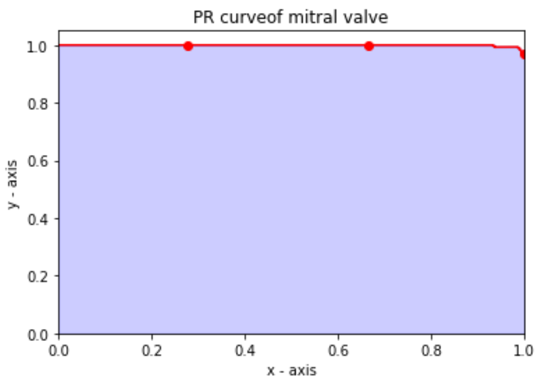


Fig 5 pr curve

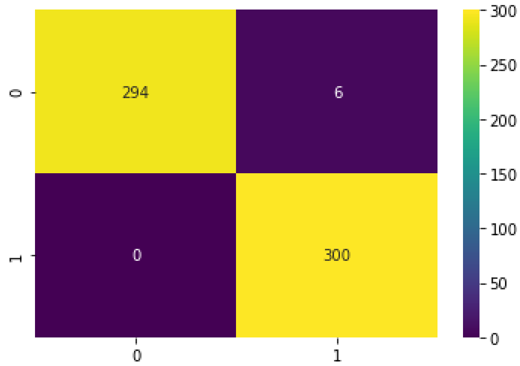


Fig 6 confusion matrix

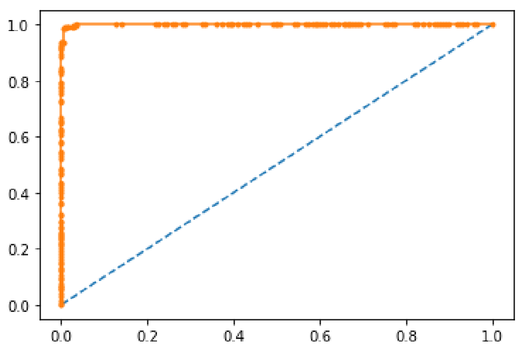


Figure 7 ROC curve

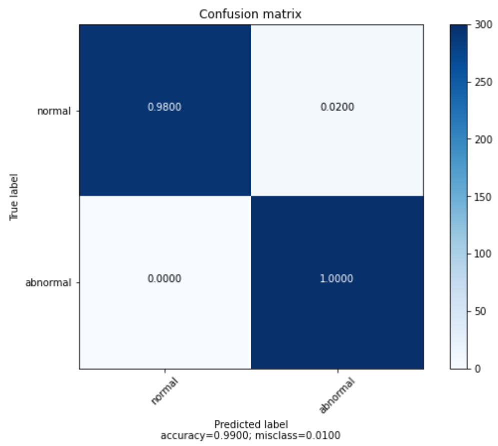


Fig 8. Normalize confusion matrix

From the PR curve and ROC, we can see 99% of accuracy also misclass is .0100

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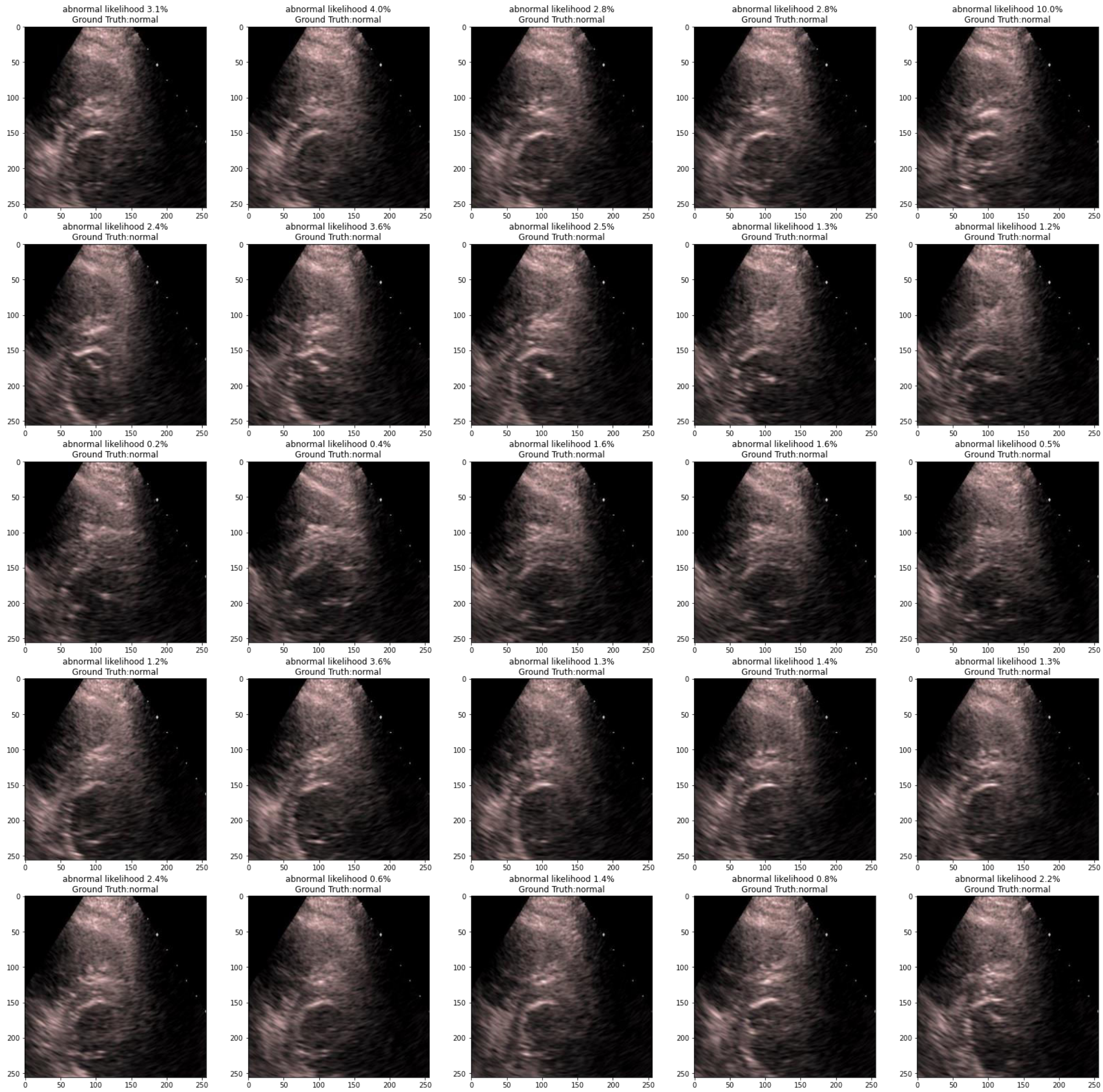
### 7. The output of the testing result




8. **Conclusion:** the proposed model efficiently and accurately detects mitral stenosis. It will help sonographers to save time. If someone has seen by stenosis, further investigation should do otherwise, not needing further research. Even a small dataset model shows promising results. Taking the PSAX view is not difficult, and it is the easiest way to detect abnormalities in the mitral valve. We use the minimum parameter model. It is possible to create an app that works in real-time if our future work is to build an android and ios app that is directly and quickly for sonographers for making a decision. This study also shows deep learning technique works perfectly for the detection of normal and mitral stenosis valve.

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