# Automatic Classification of Left Ventricular Function of the Human Heart using Echocardiography

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## ABSTRACT

This paper presents a novel approach in classifying the left ventricular (LV) function of the human heart into two categories; normal and abnormal, based on the echocardiography video recordings. Video recordings were obtained by medical doctors specially trained in adult echocardiography of the National Hospital, Sri Lanka.

Algorithms were developed to extract three features of the heart; left ventricular horizontal diameter, vertical diameter and ejection fraction. Based on these parameters, an artificial neural network (ANN) was trained and tested to automatically classify the left ventricular function as normal or abnormal. Normal or abnormal condition of the heart as decided by the cardiologist was considered as the expected output for supervised learning of the neural network. The trained ANN was able to identify the condition of the left ventricle with 95% accuracy.

## 1. INTRODUCTION

Combination of medical science with modern technology is very useful for non-invasive decision making for clinical purposes. Echocardiography is a widely used non-invasive technique for imaging the heart. A transducer is used to send ultrasound waves through the chest that are reflected (echoes) by different parts of the heart. These echoes are digitally converted and displayed in a video screen. By analyzing the video, an expert (cardiologist) can determine the condition of the heart and the problems associated with it [1].

Echocardiography machine is a very sophisticated device with the ability of viewing the heart in different angles and modes [1]. Before taking a decision, doctors examine the images of each view and manually record the parameters. The accuracy of the decision is highly dependent on the experience of the medical doctor. Therefore, automatic identification of the heart condition, based on numerical values of LV function would be of great importance to assist with the decision making process.

Image processing algorithms based on wavelet analysis [2] and fuzzy logic [3] have been developed for boundary detection in echocardiography images. Bayesian networks [4] and K-NN classifiers [3] have been used to automatically identify the heart condition. Although artificial neural networks (ANNs) have been used for many classification problems, the feasibility of using ANNs in classifying echocardiography videos has not been explored [5].

The aim of this study is to develop an automated medical decision support system based on ANNs to classify the human heart into two categories; normal and abnormal.

## 2. THEORY

Out of the four chambers of the heart, the left ventricle is the most important since blood is pumped to the body from this chamber. Therefore, accurately diagnosing the problems in the left ventricle is of significant importance. End systolic volume (ESV), end diastolic volume (EDV) and ejection fraction of the left ventricle are important parameters in determining the heart condition and can be calculated using Eq. 1 and Eq. 2 respectively [3].

$$Volume = \left(\frac{7.0}{2.4+D}\right) D^3 \ldots\ldots\ldots\ldots\ldots.. (1)$$

where, *D* is the average endocardial diameter from short axis view.

$$Ejection\ \ Fraction = \frac{EDV-ESV}{EDV} \ldots\ldots(2)$$

## 3. METHODOLOGY

When the patient is laid supine, the cardiologist scanned the patient until appropriate images appeared on screen. The transducer placement was adjusted until clear visualization was made possible.

Echocardiography can view the heart two-dimensionally or three-dimensionally and the velocity of the blood flow can be viewed using Doppler ultrasound. When a patient is examined, all these views are taken into consideration before the decision is made. However, processing all the views computationally is unrealistic. Therefore, since the cross section of the left ventricle could be clearly observed using short axis mid cavity view and the contrast between the heart cavity and the muscles is comparatively high, in this study, only short axis mid cavity view was analyzed [1]. The echocardiography screen showing B-mode (two-dimensional view of the heart) to M-mode (one-dimensional view of the heart) conversion is shown in Fig. 1. The M-mode displays cardiac function in relation to time including both the diastole and systole [1]. The cardiologist manually selected the appropriate points to generate the variables in the M-mode view. The current method of decision making used by experts requires M-mode conversion which allows the cardiologist to manually select the points of interest on the image and measure corresponding values. However, the developed automatic classification system does not need M-mode conversion since it can extract the heart cavity volume computationally.

One scanned video of a patient could be stored in the machine for few seconds by default. The hard drive data were saved as DICOM files which were compatible to read from DICOM readers or related software. The "*RadiAnt DICOM Viewer*" was used to convert the DICOM file to .jpg files. The full screen of echo also contained some unnecessary details and therefore the image was cropped before analysis. Subsequently, the images were imported to MATLAB software.

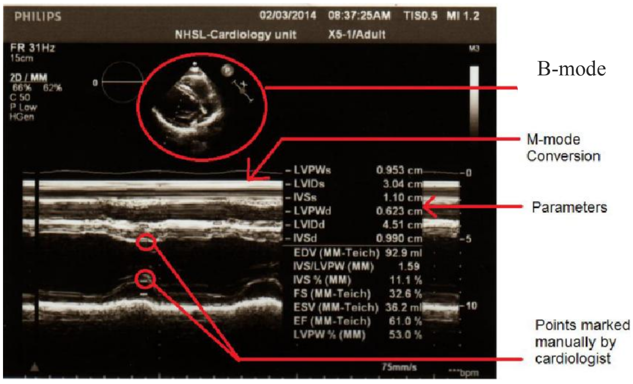


Fig. 1: B-mode to M-mode conversion while obtaining the echocardiogram.

### 3.1 Image Preprocessing

RGB images directly obtained from the echocardiography machine were converted to grey scale images (Fig. 2). Since unprocessed images were not sharp and brightness was not enough to analyze images digitally, image-enhancing techniques were applied using MATLAB software. Inbuilt functions of MATLAB (***adapthisteq***) were used to perform contrast limited adaptive histogram equalization. This method operates on small data regions (tiles) rather than the entire image. The image was divided into small tiles and the contrast of each tile was enhanced so that the histogram of each output region approximately matched the specified histogram (uniform distribution by default) [6].

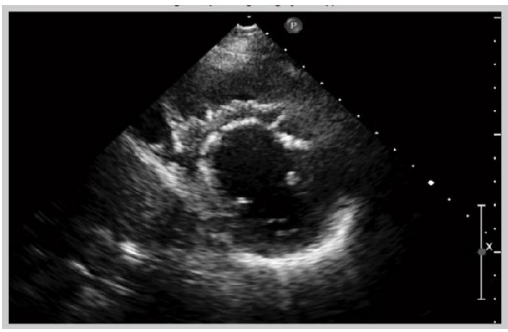

Fig. 2: Image converted to gray

Feature extraction algorithm was developed to accurately isolate the cavity area from the rest of the image. Ideally, the cavity center should lie in the middle of the image, but generally it is not. Since placing the transducer is performed manually, the cavity center can vary from image to image. Hence, the feature extraction algorithm was developed based on the following two assumptions about the image (Fig. 3).

1. All pixels inside the cavity are in an equal pixel range
2. Cavity center is close to the mid vertical line of the image

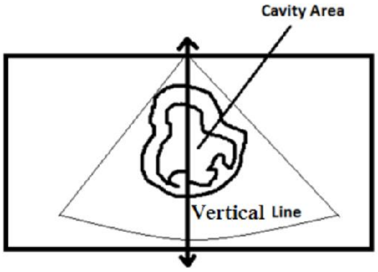


Fig. 3: Image compatible to be analyzed using the developed system. The cavity center is closer to the mid vertical line.

Contrast enhanced image (Fig. 4a) was subjected to a filtering process. To identify the dark regions of the image, initially, a Gaussian kernel was applied. Then ***imclose*** inbuilt function in MATLAB was applied which performs morphological closing on the grey scale image, returning a closed image (Fig. 4b). The regional minima of the image were found using MATLAB ***imregionalmin*** function (Fig. 4c). Based on the second assumption, the center of the image was cropped and an algorithm was applied to identify the coordinates of the pixel of the left ventricle cavity center (Fig. 4d).

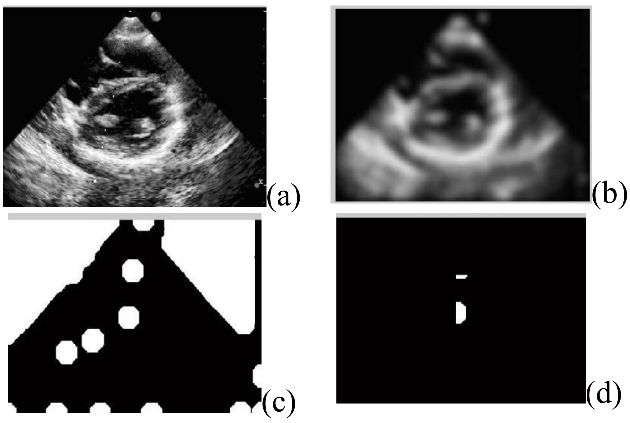


Fig. 4: Steps of detecting the cavity center. (a) Contrast enhanced image, (b) Gaussian filtered image, (c) Image after identifying regional minima, (d) Center of the image cropped.

Once the center of the left ventricle was found, the eight neighbors of that pixel were considered as the cavity center to calculate a mean value.

The boundary detection process was made more efficient by differentiating between the boundary and the cavity. The image pixels were smoothened so that the neighboring pixel values differed slightly (Fig. 5). If the majority of pixels in a particular area were dark, the neighboring pixels were made darker and if the majority of pixels were light colored, the light color in that region was enhanced. By applying this technique, the contrast between the cavity and the border was improved and hence, the image consisted of two types of pixels; pixels with the mean value of the cavity center and original pixel values of the image.

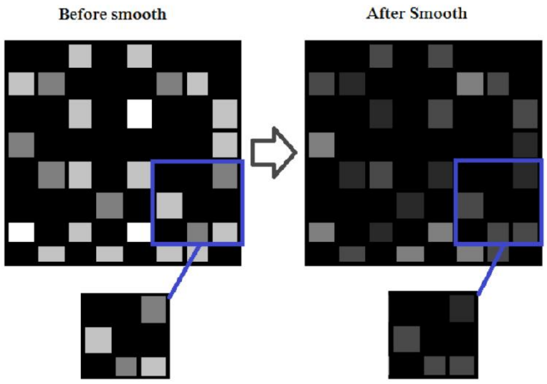


Fig. 5: Smoothening pixel colors by making dark areas darker and light areas lighter.

### 3.2 Feature Extraction

The identified center was used as the seed point and was allowed to grow until the cavity border was found. Since there was a huge pixel value difference between the cavity and the border, the image consisted of two main parts; cavity region and white background depicting blank pixel values. The Canny edge detection algorithm was applied [7] to detect the cavity edge/border.

Vertical and horizontal diameters of the heart cavity were automatically calculated by averaging the extracted cavity area. The calculated diameters were used to calculate the area of left ventricle and ejection fraction (Eq. 1 and Eq. 2).

The developed system was further improved to analyze the images that did not satisfy the two assumptions made using manual commands. After automatically finding the cavity center, the software was made to prompt for 8 seconds to give time to the user to determine whether the cavity center was correctly identified. If the center was not correctly identified, the user was allowed to manually select the center.

### 3.3 Training and Testing the Neural Network

A two layer neural network with 20 neurons in the first layer and 5 neurons in the second layer was created. Data extracted from images of 20 patients (10 normal patients and 10 heart patients) were used to train the network. The training set consisted of 20 vectors (one vector from each image) containing three elements; calculated values of vertical diameter, horizontal diameter and ejection fraction ($3\times20$ matrix). The input was targeted to an output matrix which consisted of two rows with zero or one.

During the training process, the network learns the desired output of a particular input and adjusts weights accordingly. The network was trained using supervised training. Supervised training involves giving the desired output to the network as an input [8]. The decision made by the cardiologist (whether heart is normal or abnormal) was used as the target output of the network. The output was; “1” for normal condition and “0” for abnormal condition for standard output class.

The performance of the trained ANN was tested using data from 8 patients. The decision made by the cardiologist was compared with the system's output. The given output was considered as 'normal' if 0.75 < output < 1.25 and 'abnormal' if -0.25 < output < 0.25.

## 4. RESULTS

Once the diameter was found, it was converted to volumesusing Eq. 2. Moreover, ejection fraction was calculated using Eq. 2. Classification was obtained from the cardiologist based on short axis view (Table 1).

Table1: System calculated values of end systolic volume, end diastolic volume and ejection fraction with classification by the cardiologist (training set for the neural network)

| Sample ID | End Diastole Volume | End Systole Volume | Ejection Fraction | Classification by the cardiologist(1=normal heart, 2=abnormal heart) |
|---|---|---|---|---|
| 1 | 65.483215 | 14.697295 | 77.5556301 | 1 |
| 2 | 18.68639 | 4.951441 | 73.50242075 | 1 |
| 3 | 23.522257 | 3.590875 | 84.73413925 | 1 |
| 4 | 78.882517 | 17.127209 | 78.28769967 | 1 |
| 5 | 36.229633 | 19.223126 | 46.94087572 | 2 |
| 6 | 87.318594 | 7.176496 | 91.78125108 | 1 |
| 7 | 58.283175 | 5.72966 | 90.16927269 | 1 |
| 8 | 63.379887 | 9.893 | 84.39094724 | 1 |
| 9 | 27.975345 | 10.651284 | 61.92617464 | 1 |
| 10 | 73.700874 | 52.470787 | 28.80574659 | 2 |
| 11 | 67.085005 | 20.884657 | 68.86836783 | 1 |
| 12 | 106.943708 | 43.51495 | 59.31041591 | 1 |
| 13 | 24.132218 | 11.042492 | 54.24170294 | 2 |
| 14 | 131.534311 | 57.563863 | 56.23661799 | 2 |
| 15 | 98.179674 | 46.106107 | 53.03905063 | 2 |
| 16 | 76.100524 | 49.700311 | 34.69123682 | 2 |
| 17 | 125.534311 | 63.533863 | 49.38924467 | 2 |
| 18 | 40.338611 | 22.243126 | 44.85896899 | 2 |
| 19 | 30.338511 | 18.443137 | 39.2088264 | 2 |
| 20 | 100.717134 | 57.477136 | 42.93211719 | 2 |

System calculated values for the testing set of data and a comparison between the expected output (cardiologist's decision) and system output is given in Table 2.

Table 2: System calculated values of end systolic volume, end diastolic volume and ejection fraction with classification by the cardiologist and the trained neural network (testing set for the neural network)

| End-diastole volume | End-systole volume | Ejection fraction | Expected output | System output |
|---|---|---|---|---|
| 78.882517 | 17.127209 | 78.28769967 | Normal | Normal |
| 92.947951 | 36.279432 | 61.00379146 | Normal | Normal |
| 67.540121 | 19.776423 | 70.86979849 | Normal | Normal |
| 27.975345 | 10.458703 | 62.6146 | **Abnormal** | **Normal** |
| **651.393259** | 96.213699 | 85.2296 | **Normal** | **Abnormal** |
| 94.268877 | 78.297458 | 16.9424 | Abnormal | Abnormal |
| 41.417962 | 19.768401 | 52.2709 | Abnormal | Abnormal |
| 81.842818 | 36.229633 | 55.7327 | **Abnormal** | **Data error** |

Confusion matrix [8] contains information about actual and predicted classification by a supervised learning system. The confusion matrix for the system gives 95% accuracy as shown in Fig. 6.

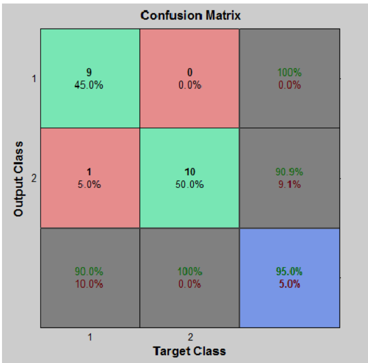


Fig. 6: Confusion matrix for the trained system; the square in the bottom right hand corner shows the correctly identified cases

## 5. CONCLUSION AND DISCUSSION

A new technique to identify the left ventricle mid cavity area from echocardiography images is presented. This technique could be successfully used to extract parameters of the human heart. According to the confusion matrix (Fig. 6), the total percentage of correctly identified cases is 95%. Hence, these results show that artificial neural networks can be successfully used as classifiers in medical decision support systems. The developed system is capable of classifying the left ventricular function into two categories, normal and abnormal. Input for the system should be an echocardiography image taken in the short axis view. The system is developed for not normalized inputs and can be used in real time.

Performance of the ANN should be improved by training with more data before practical use. The network should be tested with a bigger set of testing data in order to make solid conclusions on performance. Although system analyses only one view of the heart, decision of the cardiologist is based on all the views and modes. Hence, there is a possibility of improving the automatic classification by taking more views into consideration. If the patients were categorized according to gender, age etc., separately trained artificial neural networks could be trained to give better classification.

Although the system platform is supported by windows and MATLAB, the echocardiography machine runs on a different platform. Hence, it will be a huge advantage if these two platforms were embedded with suitable plug-ins to the echo machine.

A further potential development of this system in medical decision support systems would be to combine a video obtaining process with the decision making process. By implementing a graphical user interface for the hybrid system, it is possible to embed the developed system to the echocardiography machine with proper system compatibility knowledge.

## REFERENCES

1. Rimington, H. and Chambers, J., *ECHOCARDIOGRAPHY A Practical Guide for Reporting*, United Kingdom: Informa Healthcare (2nd ed.), (2007)
2. Hassanzadeh, M. R., Ardeshir, G. R. and Mollaei, M. R., *Two New Methods for Finding Endocardial and Epicardial Boundaries in Echocardiographic Images Using Wavelet Analysis.* European Journal of Scientific Research, (2009) 264-274
3. Ahanathapilla, V. and Soraghan, J. J.,*Myocardial Ischemia Detection Algorithm (MIDA): automated echocardiography sequence analysis for diagnosis of heart muscle damage.* Computing in Cardiology, (2010) 405-408
4. Qazi, M., Fung, G., Krishnan, S., Rosales, R., Steck, H., Rao, R.B., Poldermans, D. and Chandrasekaran, D., *Automated HeartWall Motion Abnormality Detection From Ultrasound Images using Bayesian Networks*. IJCAI, (2007) 519-525
5. Basu, J. K., Bhattacharyya, D. and Kim, T., *Use of Artificial Neural Network in Pattern Recognition.* International Journal of Software Engineering and Its Applications, (2010) 23-33
6. Pizer, S.M., Amburn, E.P., Austin, J.D., Cromartie, R., Geselowitz, A., Greer, T., Romeny, B.H., Zimmerman, J.B. and Zuiderveld, K., *Adaptive histrgram equillization and its variations.* Computer Vision, Graphics and Image Processing, (1987) 355-368
7. Nixon, M. S., Aguado and A. S., *Feature Extraction and Image Processing.* Oxford: An imprint of Butterworth-Heinemann, (2002)
8. Kalyan, K., Jakhia, B., Lele, R. D., Joshi, M. and Chowdhary, A., *Artificial Neural Network Application in the Diagnosis of Disease Conditions with Liver Ultrasound Images.* Advances in Bioinformatics, (2014)