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Pretrained DcAlexnet Cardiac Diseases Classification on Cognitive Multi-Lead Ultrasound Dataset

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Abstract: The DcAlexNet CNN deep learning classifier can easily track patterns in medical images (brain, heart, spinal cord and etc.) precisely. According to WHO (world health organization) every year 5 billion people are affecting heart diseases and heart-attacks. Heart abnormalities sometimes tends to death; therefore, an efficient medical image pre-processor and deep learning classifier is needed for diagnosis. So that in this research work multi-class DcAlexNet classifier, RRS-HSB segment-filter has been implemented. The RRS (Restrictive Random segmentation) and GHSB (Gaussian Hue saturation brightness filtration) modules are fused to get multi-level feature. The training process has been incorporated to EchoNet dataset and testing process can be verified to real time samples. The segmented features as well as filtered feature are loaded into weighted .CSV file. The following features are classified tends to get predicting abnormalities in heart ultra sound image. The pretrained DcAlexNet CNN model is loading to EchoNet 1 lakh samples using 165 layers such as normalized layer, dense layer, flatten layer, max pooling layer and ReLu layer. The computer aided design with corresponding CNN layers has been finding hidden sample over to get heart abnormality location. The experimental results in terms of Dice score 98.89%, Accuracy 99.455, precision 99.23%, recall 98.34%, F-1 score 98.92%, CC 99.27%, and sensitivity 99.34% had been attained. The attained performance metrics are competed with present technologies and outperformance the application accuracy on heart diagnosis.

Keywords: segmentation, filtration, DcAlexNet, CNN

1. Introduction

Heart disease (HD) is an extensive health problem and it is currently world's foremost issue in medical field. According to WHO (World Health Organization) HD kills 17.9 million people each year accounting for around 32% worldwide [1]. HD and stroke are major cause for cardiovascular disease, nearly 35 percent of deaths, happening every year. Cardiovascular disease is abnormal system, it is caused by a blockage of valves in heart, including high BP, diabetes, smoking and less exercise. As of now the focus of research has always been on strategies to reduce fatalities from heart failures and studies explained in [2]. The HDs detection and pre-intimation is a grateful job to researchers and doctors, as a result, early diagnosis of this heart is simplifying the treatment. The heart attacks are physically affecting abnormality in medical field and it is happening with static BP, cholesterol, blood sugar, maximal heart rate, chest pain and CVD. In order to determine the patient's cardiovascular health a traditional analysis is used to get information of heart disease, on the other hand, it is noticed that the following mechanism is time consuming process. To overcome this challenges, AI (artificial intelligence), DL (Deep Learning), ML (Machine learning) multi models are incorporated. The following methods are easily training large volumes of dataset data and predict the input whether tested sample had disease or not. The conventional methods with bio markers models are superior in operations and

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track heart disease in Ultrasound image with less time. The bio markers and CNN models are now trending in medical image processing to get micro features effectively. Most of the doctors follow the American Heart Association's (AHA) guidelines, which examine 4 well-known risk factors such as hypertension, cholesterol, smoking, and diabetes. This risk assessment model is problematic because it assumes a linear relation between each risk parameter so that outcome of heart disease detection is complex [4]. The disease prediction, classification are simplifies the diagnosis process, so that easily start treatment and get back patient's condition to become normal. Doctors must also be able to evaluate diagnostic tests sometimes correlation of HD is complex. 20 HD medical test consequences are available that differ from patient to patient and necessitate a high level of skill diagnostic. Machine Learning (ML) data analysis techniques can reduce the need of human expertise and reduce the risk of human diagnosis mistakes while improving HD prediction accuracy [5]. Flexible prediction models based on learning classes associations can easily extract input dataset by means of ML algorithms. The typical diagnosis paradigms, such as 25 AHA guidelines, can be oversimplified as a result of this doctors unable to find exact heart abnormality. A neural network technique with 76 percent accuracy has been shown to get proper forecast i.e., 7.6% it is more existences than AHA technique [6].

The contribution of this paper is as follows:

- To collect ultrasound-based heart image dataset
- To pre-process and segment the input image using GHSB and RRS models.
- To fuse the segmented image by feature fusion technique Locally Embedded Analysis (LEA)
- To classify the fused image using DcAlexnet CNN.

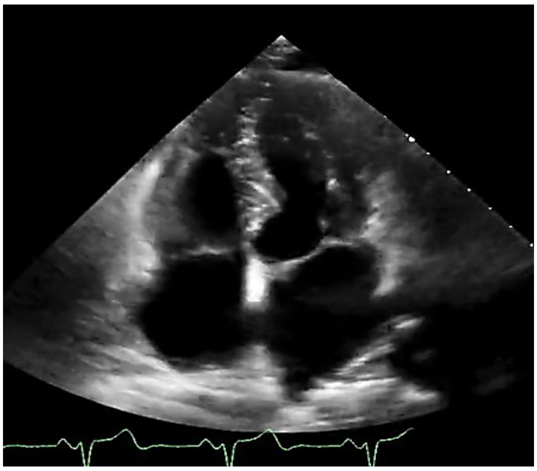


Fig. 1 - Heart ultrasound image

The above figure 1 clearly explains CAB in heart image, in this Blood clots, are stopping the oxygen saturation level and sometimes getting breathing issues causes to death. The following problem needs to be overcome using advanced Deep learning technologies.

2. Related Works

To develop a heart disease prediction systems, researchers uses a variety of data mining techniques. The UCI Cleveland database was utilised to authorize important features as well as mining processes, while UCI Statlog dataset was used for evaluation as well as verification in [7]. Vote system technology has best performance among them, with an accuracy rate of 87.41%. Similarly, in [8], XGBoost method and LR (logistic regression) approach were evaluated in terms of predicting value of CHD (Chronic Heart Disease). The demonstration of LR model has a higher accuracy of 85.86 % than XGBoost, which has an accuracy of 84.46 %. The author [9] compared three methods: KNN, SVM and NB using UCI machine learning repository, this Experiments have shown that SVM with linear kernel produces finest results with an accuracy of 86.8%. The study [10] looked at 14 variables and utilized existing dataset from Cleveland database of UCI-CPR. This model looked at four ML techniques such as NB, kNN, RF and DT. KNN classification has best effect, according to the testing results 87.34% accuracy had been attained. In the process of cardiac disease prediction, the decision tree (DT) is also crucial. Researchers in [11] tested and analysed three methods: NB, SVM and DT finding that they attained an accuracy of 81.58.00%, 61.2600%, and 90.7900% respectively. Comparing to DT 20-fold SGD model has a better than other methods. In a related study, [12] evaluated a variety of ML approaches including NN, KNN, SVM, DT CN2 rule inducer and SGD. Results of cross-validation with multiples illustration that DT and SVM have best 10-fold and 20-fold cross-validation accuracy (87.69 percent) and SGD has best 5-fold cross-validation for small dataset. Mixed models are also used in some studies to make predictions on this UCI Cleveland dataset, work [13] used RF, DL and mixed model (RF-DT). Mixed model, with an accuracy of 88.7%, was found to have the best effect in the process of heart diagnosis [14]. The planned techniques for predicting heart disease are using ultrasound image at all times in cardiac cycle without further scanning allowing for both validation and testing. The extraction a dense motion of ultrasound labelled images and its pre-processing plays an important key role before classification and feature extraction. Author of [15] created a standard database for researchers to compare techniques in the field of LV segmentation in 3D cardiac ultrasonography. The suggested platform will allow for a consistent evaluation and rating of existing state-of-the-art segmentation systems, as well as a faster heart diagnosis of technological breakthroughs. The goal of this study is to describe the technical components of database production, provide an overview of the ranking approach, and provide an overview of the task itself. In [16] explaining about medical image enhancing methods used for cardiac MRI and ultrasound images. The above all survey giving clear picture of heart diagnosis methodologies and its prediction processes.

Technique	key point	Limitation	Measures	Advanced model
Heart disease estimation	A brief survey on heart disease	This study cannot work on low quality ultrasound images	Accuracy=71.23% Recall=82.34% Sensitivity=71.83% F1-measure=69.23%	Deep learning
Adaptive AlexNet	The Improved AlexNet model is most suitable for advanced applications	This AlexNet model with old features can only be suitable for high quality ultrasound and CT images at abnormal extraction	Accuracy= 72.35% Recall=74.23% Sensitivity=81.98% F1-measure=75.71%	Machine learning model
Data mining features based on heart disease estimation	Intelligent models are used to extract heart disease.	The computing is more complex with the proposed design	Accuracy= 81.32% Recall=77.21% Sensitivity=74.28% F1-measure=69.34%	Un supervised intelligence models.
Semi-automated	Conventional GA is used to identify the heart diseases	The designed model is cannot operate with Ultrasound	Accuracy= 74.23% Recall=76.23% Sensitivity=81.34% F1-measure=80.27%	Intelligent ML network
Lead ultrasound image extraction	The following method is only providing pre-processing.	The hidden samples are cannot be identified.	Accuracy= 80.25% Recall=71.34% Sensitivity=72.34% F1-measure=85.29%	Deep intelligent network.

The above literature survey is explaining about earlier heart diagnosis models and their limitations. The following study suggests an advanced Deep intelligence heart diagnosis application requirement for future medical analysis.

3. System Model

This section explains that proposed DcAlexNet CNN design with heart abnormality detection to filtertion, segmentation, feature extraction and classification. The heart images dataset has been preprocessed using Gaussian HSB filter and segmenting by Restrictive Random field segmentation (RRS). The pre-processed and segmented output samples have been fused according to LEA modeling. The fusion is carried out using Locally Embedded Analysis (LEA) technique. The fused and extracted image has been classified using DcAlexnet-CNN. The overall proposed architecture is indicated in below figure-2 for better understanding.

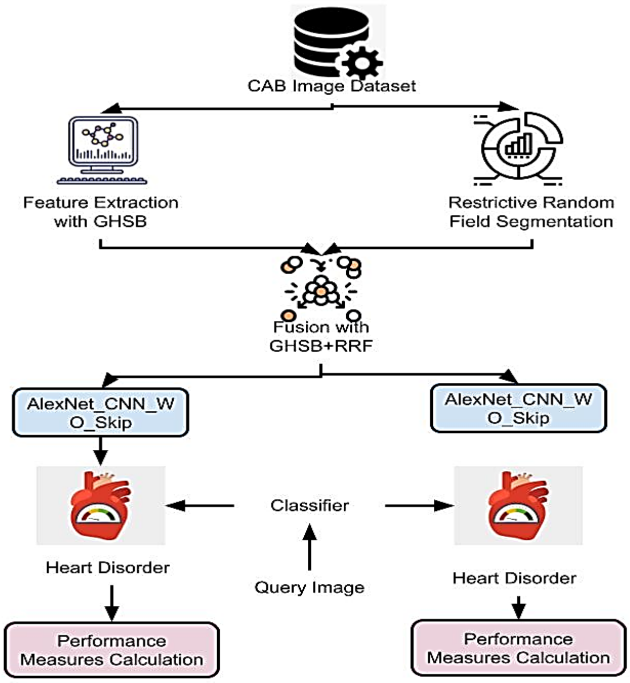


Fig. 2 - Overall proposed architecture

3.1 GHSB (Gaussian Filtration)

The gaussian filters are mainly working on RGB images but in this study calling HSB conversion and applying Gaussian parameters on heart ultrasound image. Gaussian filter is extracting high frequency noise in images and only passing noise less features to output. The implemented Gaussian HSB filter continually monitoring pixel of region (PoI) which are very useful to get deep infromation of abnormality location. The earlier filters cannot remove the pepper noise in images but propose GHSB can easily removing all noise in the images. The GHSB is a smoothing spatial idea, in this 2-D point localization realized by convolutional fitness function. The distribution of gaussian coefficients is tracking unwanted pixels and get eliminating unrelated information.

1/255

2	6	8	3	2
6	12	24	12	6
8	24	42	24	8
6	12	24	12	6
2	6	8	3	2

The stored image in the path is processed with discrete pixels according to Gaussian matrix, the non-zero kernels are taking care about less quality pixels. According to GHSB theory standard deviation (SD), Mean and variance are incorporated to find uncorrelated pixels and set them back with the help of proposed filter. The larger SD based image pixels are difficult to adjust with existed filters such as mean, median and adaptive median. So that proposed GHSB is work on Large SD and high density of noise-based pixels and giving de-noise image for further processing.

The below equation 1 is explaining about hue status and its adjustment, generally θ can be varying from 0 to 360 degrees. In this case if θ has been deciding black (B) and gray (G) pixels information according to condition. The B and G are regularly get adjust automatically and maintain ultrasound heart image quality high.

$$H=\begin{Bmatrix} \theta & if\ B < G \\ 360-\theta & if\ B > G \end{Bmatrix} \tag{1}$$

Where, $\theta = cos^{-1}\frac{3}{R+G+B}[[min(R,G,B)]]$

The below equation 2 explaining about saturation properties of input ultrasound heart image, the properties are automatically get adjust using RGB parameters and balancing medical image quality high.

$$S = 1 - \frac{3}{R+G+B}[min(R,G,B)] \quad (2)$$

The eqaution 3 explains about intensity balancing according to RGB variations. The averaging of RGB pixels giving intensity value it can get update simultaniously when training process is initiated.

$$I = \frac{1}{3}(R+G+B) \quad (3)$$

The brightness (B) is an important factor to decide picture quality, in the equation 4 brightness mathematical adjustment and it's statistical balancing has been defined. The ultrasound heart image automatically regulate it's brightness before training and classification process.

$$B = \frac{1}{2\pi\sigma^2}e^{\frac{-(R^2+G^2+B^2)}{2\sigma 2}} \quad (4)$$

3.2 RRS (Restrictive Random Field) Segmentation

The RRS is a segmentation process in which super pixels are clustered according to B & G pixel intensity. The super pixels are nothing but common characteristics of intensity group, these are useful in pattern recognition and computer vision at segmentation process. The super pixels have got segment the image into region's based on similarity as well as perception features. Generally, the RRS concentrate on watersheds, MSER's and intensity cluster for image analysis within short time before classification. The heart input image with N pixels and random field I with variables $\{I_1, I_2, \dots, I_N\}$, where i is vector made up of pixel i's spatial-feature values. Let's assume that random field X with random variables $\{x_1, x_2, \dots, x_N\}$, and xi is category label of pixel I whose value is a collection of labels $L = \{I_1, I_2, \dots, l_k\}$ defined by equation 5

$$P(X \mid I) = \frac{1}{Z(I)}exp\left(-\sum_{c\in C_g} log\,(X_C \mid I)\right) \quad (5)$$

Z(I) is a normalisation factor which ensures distribution sums to ultrasound image shown in equation 5

$$Z(I) = \sum_X exp\left(-\sum_{c\in C_g} log\,(X_C \mid I)\right) \quad (6)$$

where g = (ν,ε) represents a graph on X and c represents a set of groups. A potential φc is induced by Cg in g. The mutual interaction between pixels is evaluated by utilizing EF in each RRF step. The fully connected RRF is typically used to process the super pixel classification results provided by CNN given in equation 7

$$E(x) = \sum_i \theta_i(x_i) + \sum_{ij}\theta_{ij}(x_i, x_j) \quad (7)$$

where unary potential $\theta_i(x_i) = -\log P(x_i)$ and $P(x_i)$ indicates probability of pixel i from category label. Pairwise potential $\theta_{ij}(x_i, x_j)$ are given as equation 8

$$\theta_{ij}(x_i, x_j) = \mu(x_i, x_j)K_{ij} \quad (8)$$

f $x_i \neq x_j$, *then* $\mu(x_i, x_j) = 1$; *otherwise,* $\mu(x_i, x_j) = 0$. *Kij is given by eq.(9):*

$$K_{ij} = \omega_1 exp\left(-\frac{\|p_i - p_j\|^2}{2\sigma_\alpha^2} - \frac{\|I_i - I_j\|^2}{2\sigma_\beta^2}\right) + \omega_2 exp\left(-\frac{\|p_i - p_j\|^2}{2\sigma_\gamma^2}\right) \quad (9)$$

Pixel i and pixel j positions are represented by pi and pj. First portion of formula expresses degree to which adjacent pixels with comparable band values are classified as belonging to the same group. The weights of position as well as band value are controlled by variables σa and σβ. The second element of the formula is used to remove image parts that are substantially isolated. Values of ω1, σa, σβ, ω2 and σγ may be extracted from image by utilizing Joint Boost technique. Pixels in RRFs interact with one another via their energies, their category labels may transformation over time and crude super pixel outcomes are divided into pixel-based categorization outcomes shown in equation 9.

3.3 Algorithm of RRS

The below RRS algorithm has been separate the background and object in effective way, the clustering of RRS is giving features from object so that getting abnormal affected area on ultrasound heart image.

Input: heart input image M_{image} *superpixel classification result* ; $M_{superpixel}$ *sample set* S; *maximum number of iterations*;

N_{max} *and number of categories* ;

Output: Segmented result $M_{pixelresult}$

RRF Array[$N_{category}$] = *Initialize array with* $N_{category}$ *elements;*

for i in i: $N_{category}$ 1

State ith category as "target" and other category as "background";

M_{label} = *transform* $M_{superpixel}$ *into a two − category superpixel image with "target" and "background" categories*;

S_{object} = *transform S into a two − category training set with targetand backgroundcategories*;

M_{result} = $SBIC(M_{image}, M_{label}, S_{object}, N_{max})$;

RRFArray[i] = fetch all "target" category pixels in M_{result} *and modification their category labels into i th*

category;

$M_{crfresult}$ = *Use fully connected RRF to segment* $M_{superpixel}$ *in* N_{max} *iterations*;

M_{merge} = *Combine all pixels and their category labels in RRFArray into a result image.*

conflicting pixels;

CPixels = Obtain conflicting pixels in RRFArray and allocate each pixel.

$M_{crfresult}$*'s corresponding position pixel*;

UPixels = Obtain unassigned pixels according to RRF Array and assign every pixel

$M_{superpixel'}$ *s corresponding position pixel*;

$M_{pixelresult} = M_{merge} + (CPixels + UPixels)$;

return $M_{pixelresult}$

End

The above RRS algorithm is operated through 19 step pseudo code which is implemented on python 3.7 software tool. Simulation results of following technique can provide segmentation on ultrasound image with good accuracy.

3.4 LEA Feature Fusion and Classification

The Local Embedded Analysis (LEA) is a feature fusion technique, using LEA has been tracking global features from RRS and GHSB filtration-segmentation respectively. The proposed classifier is working on supervised learning samples, but implemented RRS and GHSB mechanisms generating non-linear un supervised features. So that calling LEA, it can provide linear supervised features easily. The high dimensional and larger data sets cannot be handled by proposed CNN model. The LEA preprocess the data and handling large dimensional dataset with optimization. The following functionality providing symmetric principal between supervised and linear samples. The below three steps has been handling the feature fusion process and generating HeartNet image for proposed classifier.

LEA has three steps:

(1). Choose neighbors: as an input, LEA takes a set of n D-dimension vectors accumulated in a matrix $X = [x_1, x_2, \dots, x_n] \in R^{D\times n}$. For each sample x_i $i = 1, \dots, n$, its KNN are identified, and their indices are kept in a $n\times k$ matrix J, based on similarities between data points evaluated by Euclidean distances.

(2). To obtain reconstruction weight matrix $W \in R^{nxn}$, where w_{ij} indicates involvement of data point x_j to data point x_j, minimise following CF by equation 10

$$e(W) = \sum_{i=1}^{n} | x_i - \sum_{j=1}^{n} w_{ij} x_j \|^2 \qquad (10)$$

where optimization are subject to constraints given by equation 11

$$\sum_{j=1}^{n} w_{ij} = 1 \qquad (11)$$

And $w_{ij} = 0$, if x_i and x_ji are not neighbors. If not, wij is indicated by optimization of modernization faults in way of explaining a least-squares issues.

(3). Map high-dimensional information to embedded coordinates: weight matrix W is kept static and low-dimensional embedding $\bar{Y}\,[y_1, y_2, \dots, y_n] \in R^{+x_n}$, where d signifies embedded dimension, obtained by reducing embedding cost function given by equation 12

$$\Phi(Y) = \sum_{i=1}^{n} \left| y_i - \sum_{j=1}^{n} w_{ij} y_j \right|^2 \qquad (12)$$

under the constraints below by equation 13 and 14

$$\sum_{i=1}^{n} y_i = 0 \qquad (13)$$

$$\frac{1}{N} \sum_{i=1}^{n} y_i y_i^T = I \qquad (14)$$

Based on matrix $\bar{M} = (I - W)^T (I - W)$, a new sparse matrix M of size $n\times n$ is generated, and low-dimensional embedding Y is given by performing an eigen decomposition of new sparse matrix M. Because eigenvalue of first eigenvector, which is near to zero, is ignored, Y are characterized by equation 15

$$Y = [v_2, \dots, v_{d+1}]^T \qquad (15)$$

Where $v_2, \dots, v_{d+1}$ indicates 2nd to (d+1)st smallest eigenvalues of matrix M.

Table 1 - Dataset features

age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
052	01	00	0125	0212	00	01	0168	00	01	02	02	03	00
053	01	00	0140	0203	01	00	0155	01	03.1	00	00	03	00
070	01	00	0145	0174	00	01	0125	01	02.6	00	00	03	00
061	01	00	0148	0203	00	01	0161	00	00	02	01	03	00
062	00	00	0138	0294	01	01	0106	00	01.9	01	03	02	00
058	00	00	0100	0248	00	00	0122	00	01	01	00	02	01
058	01	00	0114	0318	00	02	0140	00	04.4	00	03	01	00
055	01	00	0160	0289	00	00	0145	01	00.8	01	01	03	00
046	01	00	0120	0249	00	00	0144	00	00.8	02	00	03	00

The below figure 3 clearly explains about HeartNet process on ultrasound images, the ultrasound dataset is applied to preprocessor and adjusting features using histogram balancing. The resolution has been fixed to 512*512 and maintaining good aspect ratio. The HeartNet architecture is consist of 650,000 neurons 60 million specifications, Entire data has been normalized into 14 classes named such as age, sex, CP, trestbps, CHOL, FBS, restecg, thalach, exang, oldpeek, slope, CA, THAL and target shown in table 1.

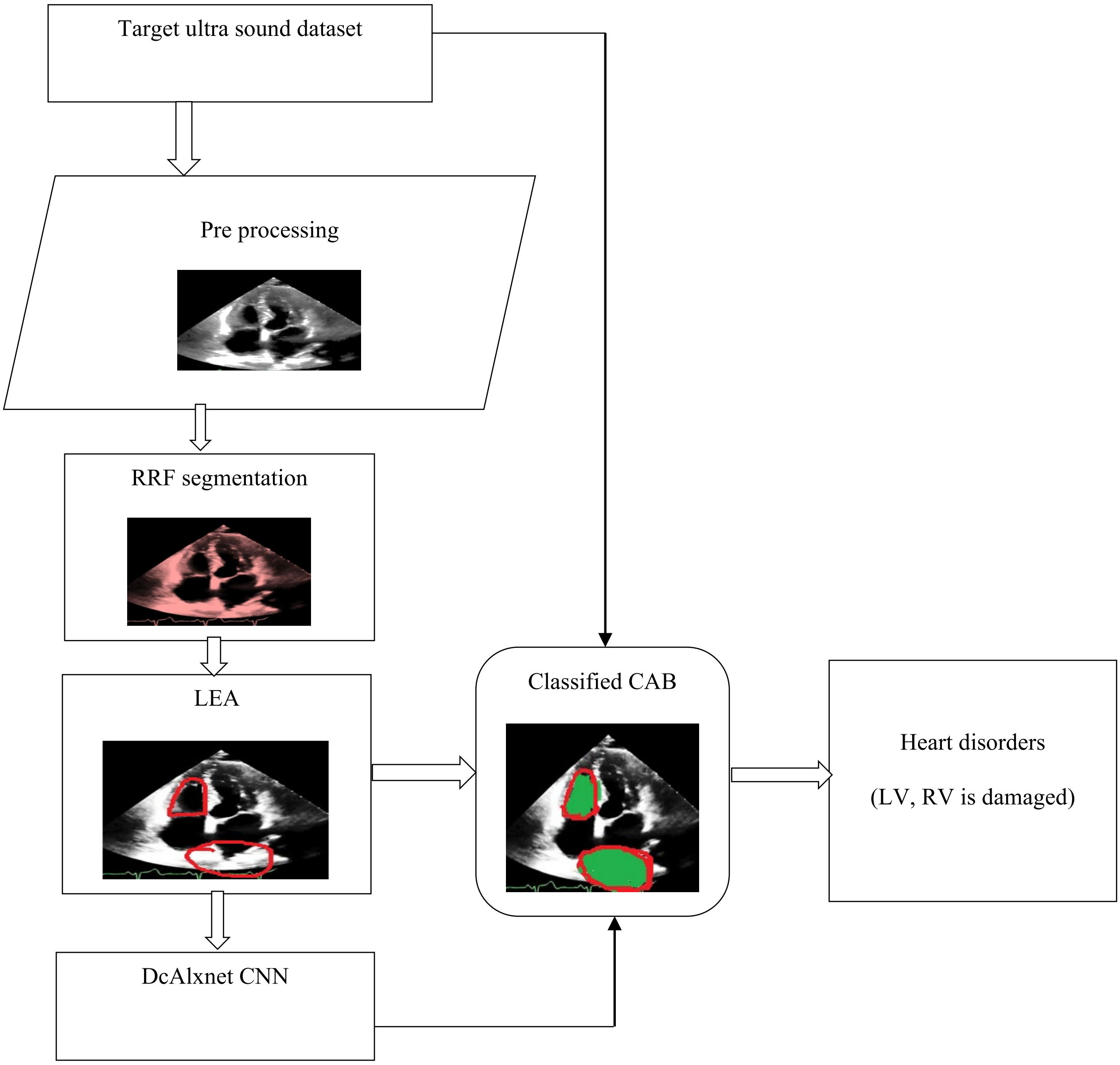


Fig. 3 - HeartNet block

The 165 layered CNN deep learning process is extracting information from ImageNet, the layers like flatten layers, dense layer, max-pooling layer, ReLu layer and Normalized layer are handling deep features. The equation 16 and 17 explains about ReLu layer functionality according to AlexNet callings.

$$ReLU\ (x) = max(0, x) \quad (16)$$

$$\bar{J}(\theta) = J(\theta) + \alpha\Omega(\theta) \quad (17)$$

The DcAlexNet consist of 165 layers architecture, these are pretrained vesrion of CNN, this design can handle millions of images for EchoNet dataset. The multi-class pretrained model at time categarized 1000 images without any distrabance. The DcAlexNet is nothing but taking 3D filteration instead of 2D filters,the identiy mapping is one more advantage functionality which is decreasing gradient problem. The percetage of training error has been improving with easy of feature extraction. The ResNet sometimes skips its connection but DcAlexNet cannot skip the connections such that extracting hidden and deep features. The ResNet-v2 152 model is facing pre training issues so that measures accuracy is diminished i.e., 78.9%.

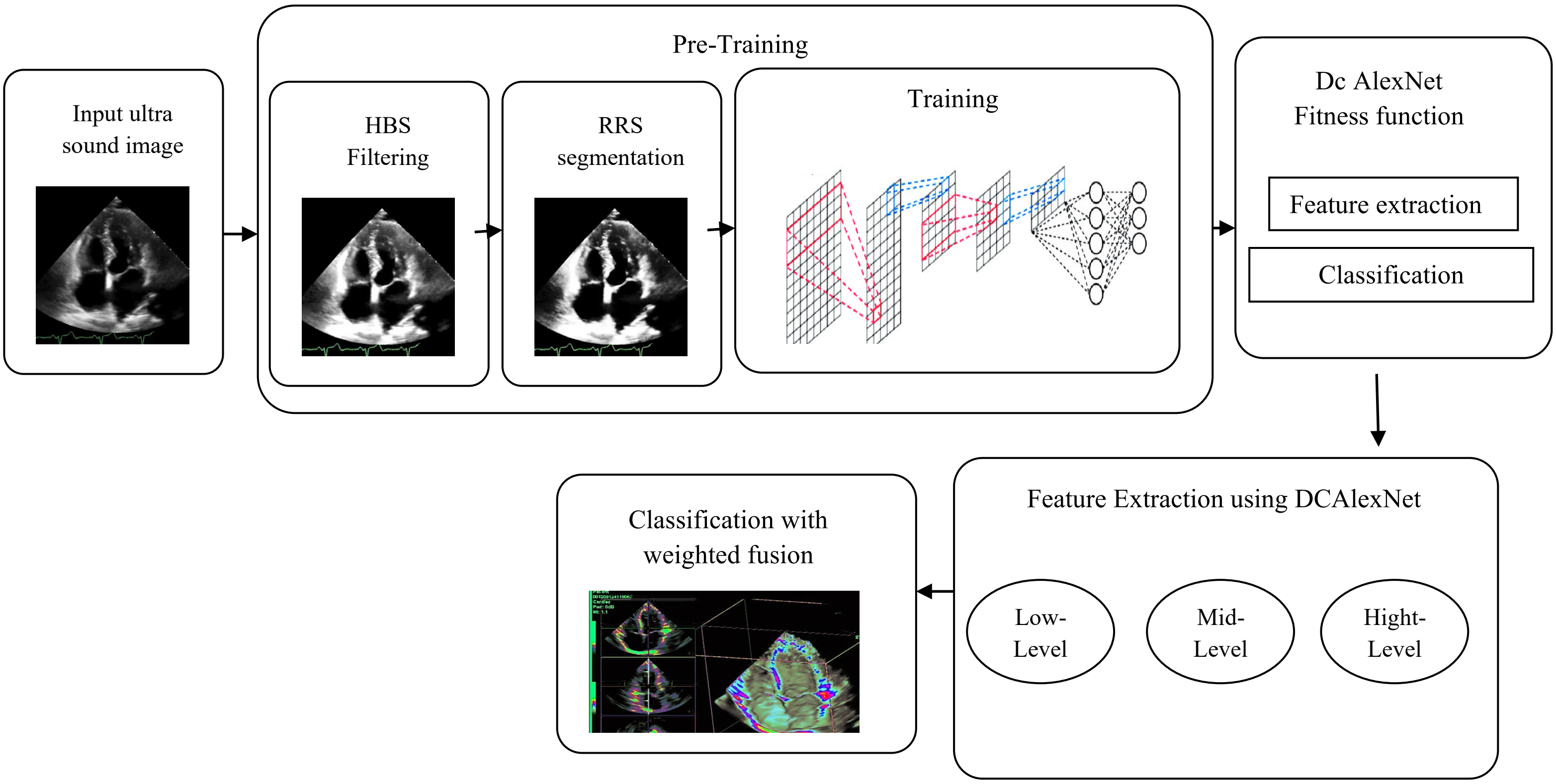


Fig. 5 - DcAlexNet CNN architecture

The above figure 5 is clearly explaining about DcAlexNet internal architectural diagram, in this pre-processing has been performed through RRS and HBS models. The feature extraction and classifications are trained to proposed deep learning model. L2 regularization is utilized in this paper to improve model generalisation, and the model weight is reduced to near zero by equation (18):

$$\tilde{J}(\omega) = J(\omega) + \frac{1}{2}\alpha \parallel \omega \parallel_2^2 \qquad (18)$$

After the convolution layer, the batch normalising (BN) layer is expanded to normalise the data to overcome gradient disappearance as well as gradient explosion issues. The BN layer normalises data by evaluating mean as well as variance of input samples then presents two specifications to restore learned feature distribution by continuously training these two specifications formula is shown in equations (19) and (20) between which are sample mean, sample variance, and a constant close to 0.

$$\hat{x}_i = \frac{x_i - \mu}{\sqrt{\sigma^2 + \varepsilon}} \qquad (19)$$

$$y_i = \gamma \hat{x}_i + \beta = BN_{y,\beta}(x_i) \qquad (20)$$

Finally, proposed DcAlexNet CNN model is efficiently extracting features with deep network architecture to find abnormalities in the heart ultrasound image.

4. Experimental Analysis

The proposed technique has been used to predict cardiac disease and results have been measured. Heart disease dataset has pre-processed for outlier removal and data normalization. In the next step feature selection module like RRS and GHSB models are imported. The combination of filtration and segmentation image features are fused through LEA module. Finally, DcAlexNet CNN deep learning is classify the heart disease and measuring affected area.

4.1 Dataset Description

EchoNet: https://echonet.github.io/dynamic/ is a heart ultrasound dataset which is collected from EchoNet organization. The Real time sample: Heart Ultra sound images are Collected from sowjanaya general Hospital Hyderabad.

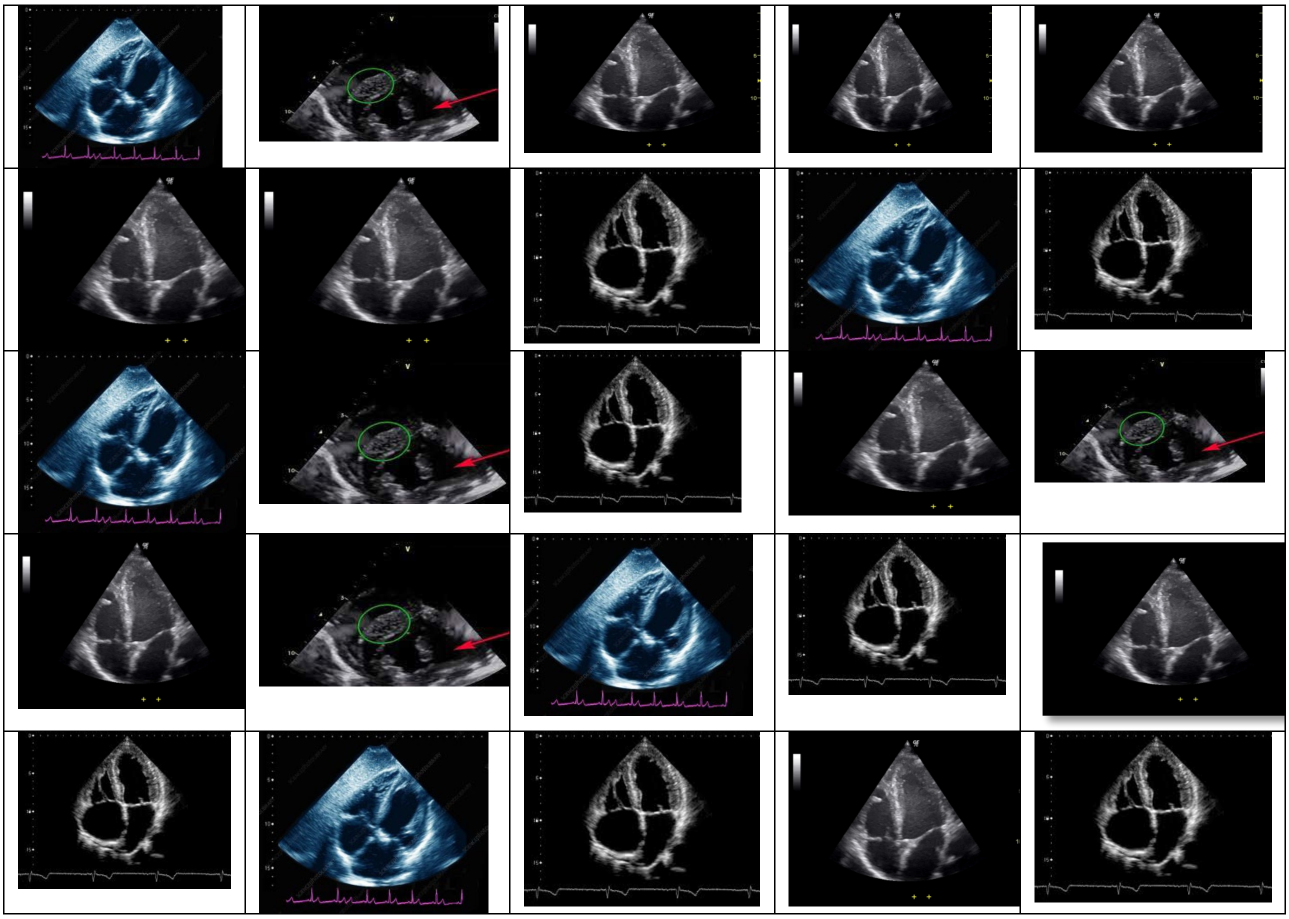
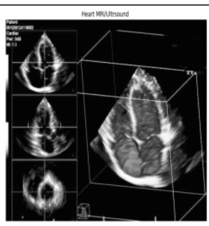
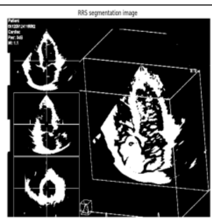
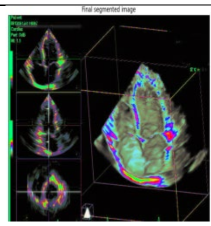
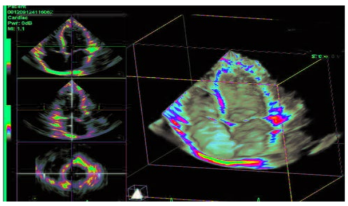


Fig. 6 - EchoNet dataset

The above figure 6 is briefly explains about EchoNet dataset which contains heart ultrasound images for CNN training. In this dataset various orientations HeartNet data is collected such as male, female, adults, old age people and etc.

Table 1 - Heart image Processing and classification using proposed model

Input image	Heart Ultrasound image	Output of GHSB model	Output of RRF based segmentation	Pre-processed & segmented image
				
Classified image 				

The above table-1 shows the heart image processing by proposed model. initially the input image has been applied to heart diagnosis. Then functional image is processed based on GHSB filtering for noise removal and image resizing. This image is segmented using RRS and LEA based feature fusion for clustering the samples the fused image is classified using DCAlexnet CNN. In equation 21 and 22 standard deviation (SD σ) is an statical parameter which is helpful in the measure of performance metrics.

$$\sigma = \sqrt{\frac{1}{N\times M}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}\left(x_{ij}-\mu\right)^2} \quad \text{------- (21)}$$

$$\sigma = \textit{standard deviation} \text{ ---------- (22)}$$

Table 2 - Comparative analysis in terms of Parametric analysis

S NO	PARAMETER	Automatic synthesis [14]	meta-analysis [15]	Iterative image deblurring [16]	LEA-CNN with RRF and GHSB
1	Dice score	71.8	89.12	70.15	74.21
2	Accuracy	91.23	91.0	89.78	99.74
3	Precision	87.45	77.91	91.48	98.81
4	Recall	84.78	81.74	86.15	98.14
5	F1 score	76.28	76	81.23	94.87
6	PSNR	40.56	41.45	44.97	59.26
7	CC	0.091	0.0897	0.0923	0.0989
8	Sensitivity	96.12	92.0	97.18	99.45

The above table 2 shows comparative analysis in terms of Dice score, Accuracy, precision, recall, F-1 score, PSNR, CC and sensitivity between proposed and existing techniques. The existing technique are attains less accuracy and attains less improvement compared to earlier models.

4.1.1. Dice Score

The dice score (DC) is an important factor in medical image analysis, DC is estimating multi-segment classification score between background and object. The training process and learning process models are using this DC score calculating image features, if this score is nearer to 100, then object detection can be accurate or necessary refinement is required shown in equation 23.

$$\text{DC} = (\text{TP})/(\text{TP} + \text{TN} + \text{FP} + \text{FN}) \text{ -------- (23)}$$

4.1.2. Accuracy

Accuracy is a performance measure using this score calculating application robustness, this metric providing spatial point based reliable information on classified image. The accuracy is work on ground truth data and differentiating classified image with Epochs as well as transfer learning shown in equation 24.

$$\text{Accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{TN} + \text{FP} + \text{FN}) \text{ --------- (24)}$$

4.1.3. Precision

The precision is a metric in which positive prediction score has been calculating for application testing. If the precision score is high, suggesting that predicting task is almost true, moreover precision giving information about experimental results and its relevancy shown in equation 25

$$\text{precision} = (\text{TP})/(\text{TP} + \text{FP}) \text{ -------- (25)}$$

4.1.4. Recall

The recall should be near to 1 then it is concluded that proposed technique is a good classifier. The recall is a very important factor compared to precision, because it predicting less false positive rate classes. The recall score is classifying the algorithm by its total relevant experimental outcomes shown in equation 26.

$$\text{Recall} = (\text{TP})/(\text{TP} + \text{FN}) \text{ ----------- (26)}$$

4.1.5. F-1 Score

F1 score is harmonic mean of Recall and precision measures, the F1 measure can giving application robustness between classifier A and classifier B. The rate performance and statical measures depending on F1-Score, usually 0 to 9 is the value, if the F1 measure is 0 said to be lowest or if F1 measure is 1 means highest shown in equation 27.

$$\text{F1 Score} = 100 \times \frac{\text{PSNR}\times\text{SSIM}\times\text{Contrast}}{\text{Std.Dev}\times\text{MSE}} \text{ ---------- } (27)$$

4.1.6. PSNR

The PSNR nothing but peak to signal noise ratio, this measure is comparing ratio between original image as well as reconstructed image. The PSNR is high means constructed image in good quality. The SSIM, MSE are also measure which are used to find image restrictive error shown in equation 28 to 30.

$$\text{PSNR} = 10 \log_{10}\left(\frac{R^2}{\text{MSE}}\right) \text{ -------- } (28)$$

$$\text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x + \mu_y + C_1)(\sigma_x + \sigma_y + C_2)} \text{ ------- } (29)$$

$$MSE = \frac{\sum_{M,N}[I_1(m,n) - I_2(m,n)]^2}{M * N} \text{ ------- } (30)$$

4.1.7. Sensitivity

The sensitivity is factor in which disease diagnostic and probability factors are estimating few false negative features. The sensitivity measure can identify positive features using spatial point related to classified image shown in equation 31.

Sensitivity =Recall= (TP) / (Total features in the image) ------- (31)

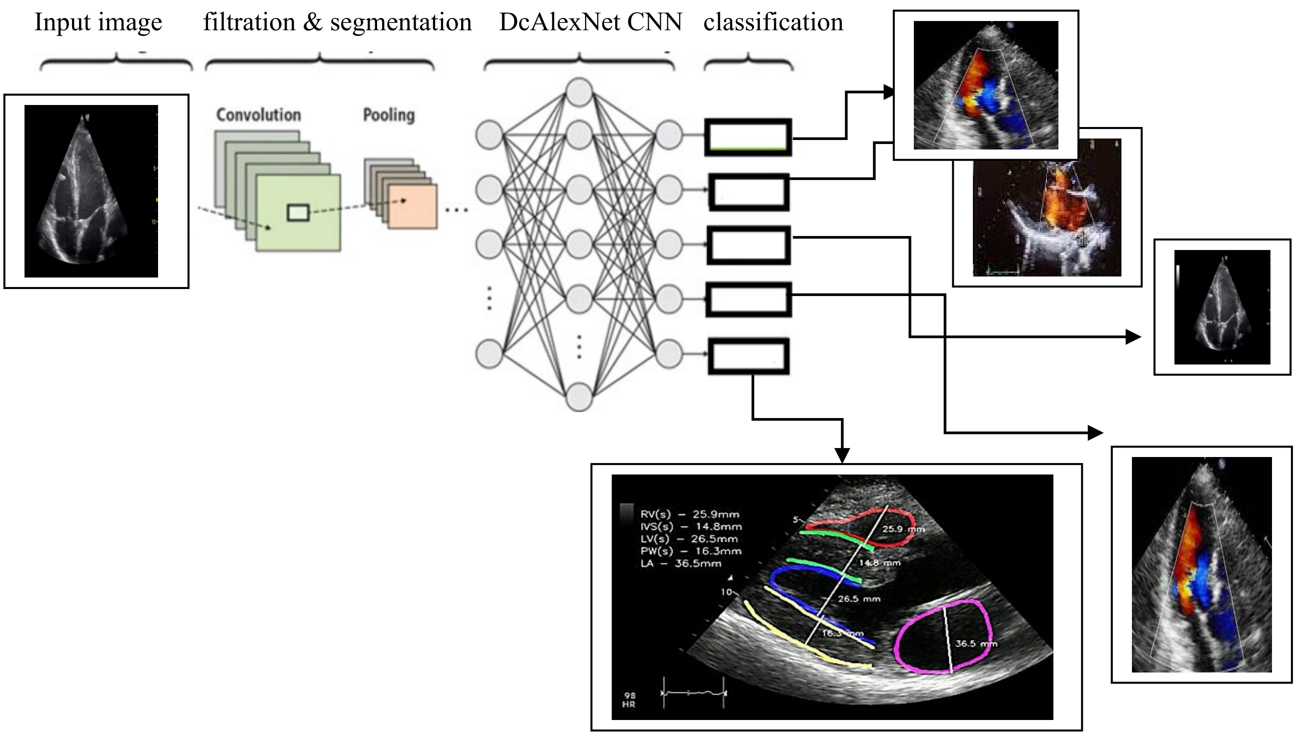
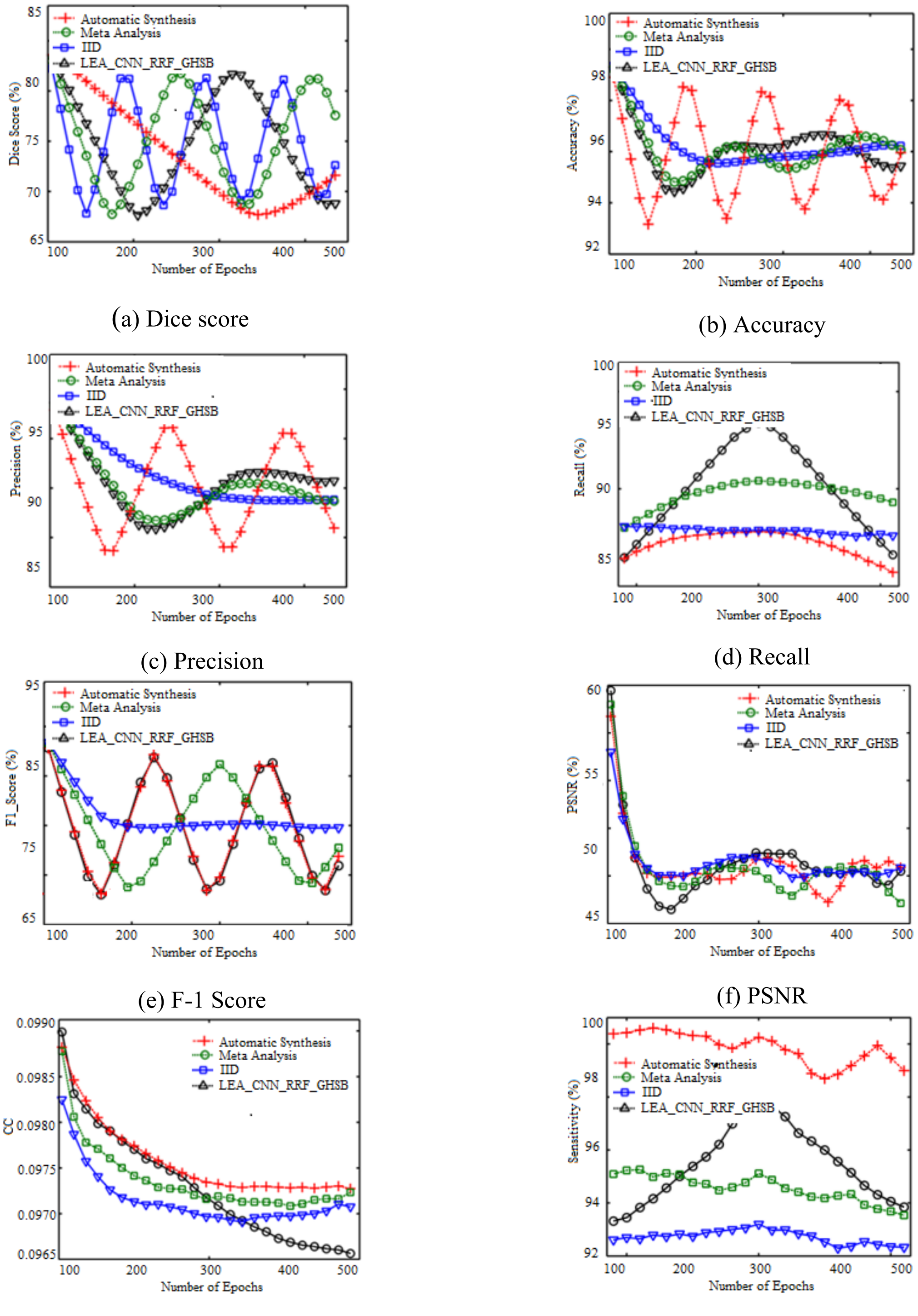


Fig. 7 - DCAlexNet classification

The above figure 7 is explaining about DcAlexNet classification on heart ultrasound images, in this input is classified and estimating the affected area using proposed technique.



(a) Dice score (b) Accuracy

(c) Precision (d) Recall

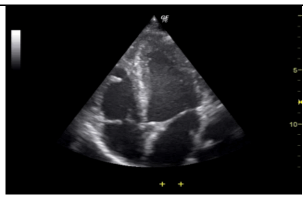
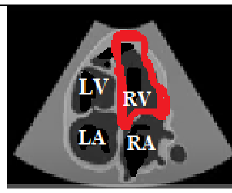
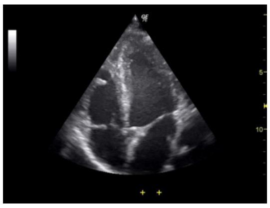
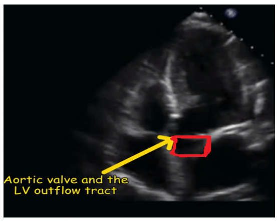
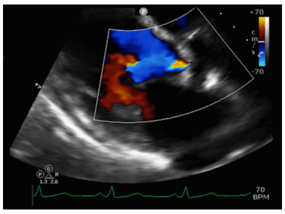
(e) F-1 Score (f) PSNR

(g) CC (h) sensitivity

Fig. 8 - Comparative analysis for proposed and existing technique in terms of (a) Dice score; (b) Accuracy; (c) precision; (d) recall; (e) F-1 score; (f) PSNR; (g) CC; (h) sensitivity

The above figure 8 shows comparative analysis between existing and proposed techniques based on the performance measures. Here the parameters like Dice score, Accuracy, precision, recall, F-1 score, PSNR, CC and sensitivity has been estimating by means of confusion matrix. The above graphical analysis is concluded that proposed technique obtained optimal results in detecting the heart blockage along with their length and width (Geometric conditions).

Table 3 - Simulation results of heart diagnosis

S.No	Image selection	Patient Details	Disorder	Test image	Classified abnormal region	accuracy
1	Heart ultrasound IMG001	male(age=35)	Heart attack			0.948
2	Heart ultrasound IMG002	Female(age=42)	CAB			0.972
3	Heart ultrasound IMG003	male(age=45)	LV blockage			0.961
4	Heart ultrasound IMG004	Female(age=47)	Heart attack			0.943
5	Heart ultrasound IMG005	Female(age=52)	RV blockage			0.953
6		AVG				0.95.54

The above table 3 briefly explains about heart abnormality detection using proposed RRS-GHSB with DcAlexNet model. The heart ultrasound images001 to image005 are applied to designed application, the implemented model can track abnormalities and classify disease. The LV, RV, heart attacks and CAB abnormalities had been classified using DcAlexNet.

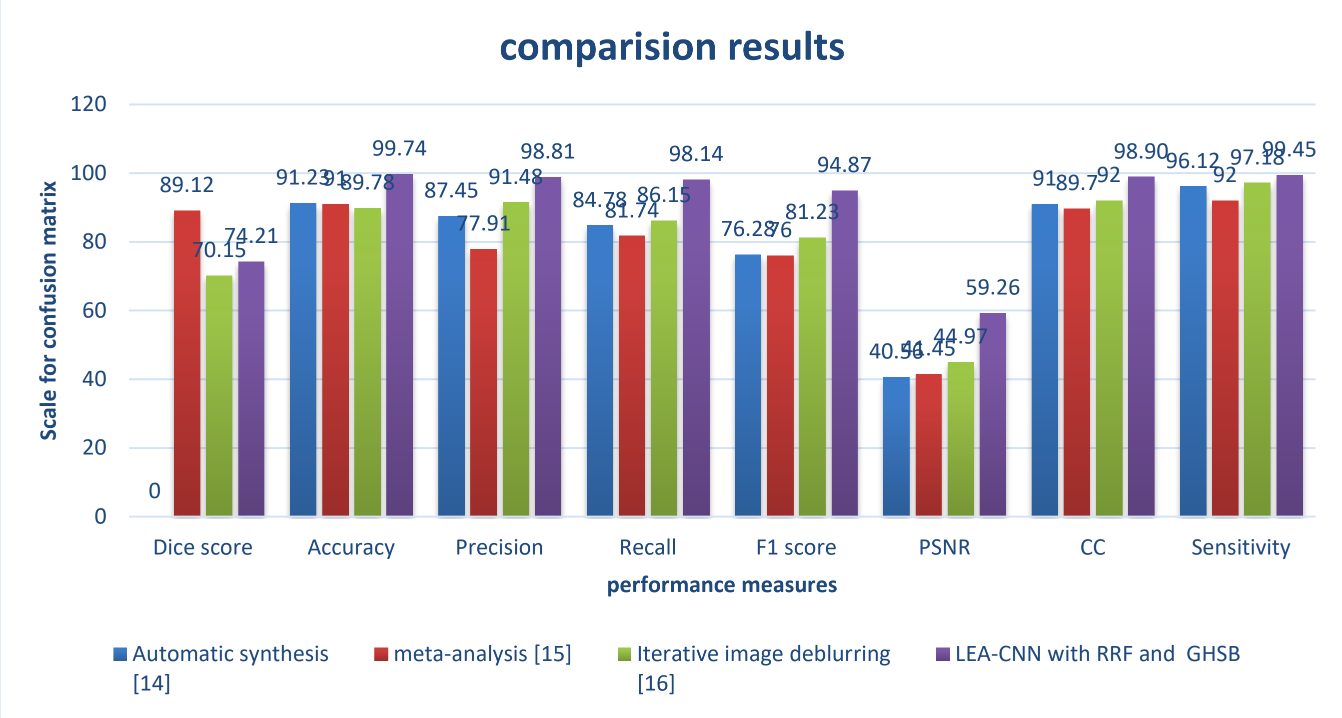


Fig. 9 - Results comparison

The above figure 9 clearly explains about comparison of results, in this related to earlier models proposed DcAlexNet technique attains more improvement. The earlier models like Automatic synthesis, meta-analysis, iterative image deblurring has been attains less performance improvement. The proposed RRS-GHSB-LEA-DcAlexNet CNN model improving performance metrics. The Automatic synthesis model can extract abnormality in the ultrasound heart images but this model hasn't dealing high density noise images and cannot classify the abnormalities. The meta-analysis based ultrasound heart abnormality recognition cannot be detect deep abnormality of disease because of

5. Conclusion

In this research work heart diseases and its abnormalities has been identified accurately and rapidly to Dc AlexNet CNN deep learner and Restrictive Random Field segmentation. The implemented framework has been functioning on ultrasound heart images employing through multi-class RRS technique. This experiment extensively conducted on EchoNet dataset; it contains 20 million heart ultrasound samples. The proposed Dc AlexNet CNN exhibit's better heart diagnosis and encouraging heart abnormalities detection. The testing process is finding whether uploaded image had disease or not according to classification. The experimental results show comparative analysis of proposed technique in terms of Dice score 98.89%, Accuracy 99.455, precision 99.23%, recall 98.34%, F-1 score 98.92%, CC 99.27%, and sensitivity 99.34% had been attained. This comparison suggesting that proposed RRS- Dc AlexNet CNN technique obtained optimal results in detection of heart diagnosis.

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