Left Ventricle Of Cardiovascular Image Segmentation Using T-Segnet Hybrid And Extended Buffalo Optimization

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Abstract
Today, cardiac disease is one of the most promising cause of mortality. The segmentation of the cardiac image is an essential process to generate personalized models of the heart and to quantify the parameters of cardiac performance. One of the important step is to perform segmentation in Left Ventricle (LR) of cardiac using magnetic resonance images (MRI).However, which can used to find important parameters to be mentioned stroke volume, dischargesection, the structure of the left ventricle myocardium. In addition, the segmentation of the left ventricle helps to build personalized cardiac computer models in order to perform digital simulations. Right now, it is observed that no automated segmentation methods related to cardiac images derived accurate performance. In this article, a new hybrid architectures is proposed where T-Net architecture can combined withSeg-Netto reduced network parameters and used for classification of cardiac MRI images .Then, in order to retrieve an approving performance, we use the EBO (Extended Buffalo Optimization) algorithm to solve the cardiac segmentation. Experimental results show that the proposed method successfully segments LR and achieves 90% accuracy in the cardiac images.

Keywords: Cardiac segmentation, left ventricle, T-Net, SeqNet and Extended Buffalo Optimization.

1. INTRODUCTION

Today, cardiac disease is the leading cause of mortality [1]. A number of cardiac imaging technologies were introduced among one is magnetic resonance imaging (MRI) used as tool forestimatingthe diagnosis and provide necessary information for the treatmenttypical conditions. The overall structure of heartis made with four important chambers, among two are left and right ventricle (LV and RV). One of the most important chamber of heart to be left ventricle (LV) [2][4][8]used to pushes blood to the complete body. It is crucial to find segmentation of LV, used to find important parameters to be mentioned stroke volume, discharge section, the structure of the left ventricle myocardium.Now a days, the manual process of LVsegmentation[2][3]is going on because methods of automation failed to meet precision specifications.Most of such automation algorithms are suffered with the issue of internal contours shrinking problem.Moreover, it is observed that region which is extracted from the LV image resulted to be small in size and produced imbalance problem between the pixels among background and LV region. Finally, also notice that in case of pathological cases, there to be drastic variability in volume and intensity of LVamong the different patients can be significant.Recently, Deep learning methods were become popular for segmentation of cardiac images with the use of fully convolutional networks (FCN) [7]. The kind of neural network which isanautomated segmentation used to perform ventricular segmentation. But the problem with FCNs are less in computational cost and leads to the degradation of expectation of user in the concerned production systems. The FCN architectures is used for cardiac segmentation [1][9], The basic phenomena kept in FCNis used to allow learn toextract desired characteristics of spatial scales by using the downward sampling path and then finally features are combine for the pixel prediction using path up sampling. AUNetis one of the FCN variant, popular whichis used for cardiac segmentation [6] and also got complete approval for usage of study in clinical .One of the most difficulty in FCN is performed sampling of the layers to be slow in case of the large images. To enhance speed of network an alternative to FCN is E-Net, introduced in [6] and is used the mechanism of sampling which results feature map with limited size. The network where computation load at the case image is of full resolution and it leads to reduction in trainingand also inference time. But both the U-Net and E-Net were made with single set of the concatenation layer among the both blocks called encoder and the decoder. An alternative to such networks called T-Net, in which all low level features from high level features are extracted from encoder and shared to decoder which helps to perform further prediction. This paper introduce a hybrid neural networks i.e., T-SegNet Architecture is used to combine the functionality of both the pooling and skipping tasks. The idea of such network is to learningfeatures relevant to multiple tasks and results lead to performance efficiency and reduce the model complexity. Further to perform segmentation of LV images applied proposed Extended African Buffalo Optimization.The material and methods described in section 2. Later, the proposed method details are mentioned in section 3. Next, in section 4 the proposed LV segmentation method evaluation is presented with the benchmarks of accuracy, Dice, Jacard index and sensitivity. At section 5 conclusion is made.

2. RELATED WORK

2.1. Convolutional Neural Network(CNN)forCardial MRI Images

Let's consider the given input image to be represented with Convolutional Neural Networkfor the purpose of image segmentation to be $X=\{x_i \in R, i \in S\}$ and resultant image to be represented as $Y=\{y_i \in L, i \in S\}$, with set of class labels to be mentioned as $C=\{0,1,2,......,c\}$ and the equivalent image to be represented with S. Next, the discriminate membership to be represented as $f_W(.)$ in the CNN model of segmentation withweights W and conditional probability distribution $P(Y|X)$.Finally result of CNN model derives probability distribution on the class labels through softmax membership function i.e., $f_W(.)$ and it can be maximizing with the probability to be represented with equation(1).

$$P(Y=C \mid f_W(X)) = soft\max(f_W^C(X)) = \frac{\exp(f_W^C(X))}{\sum_{C^{'} \in L} \exp(f_W^{C^{'}}(X))} \quad (1)$$

Where $f_W^C(X)$ to be treated as the c^{th} vector element of softmax membership function $f_W(X)$. Generally, to minimize learn optimal weights of CNN model used the negative log-likelihood membership function with weight W and to be represented as $\log(P(Y \mid f_W(X))$. The complete idea is similar to minimize the loss of cross entropy between input image ground truth, Y and output $f_W(X)$.

2.2. Fully Convolution Network (FCN)

In order to perform segmentation one of the best deep learning network is aFCN[1] architecture and is mainly composed with set of encoders and decoders and the complete structures is represented in Figure 1. The network of encoders comprises several layers applied after several layers with the consecutive operations of convolution and non-linear activation. In general encoder performs encodes to the prominent features of image in the segmentation task respectively. Later, achieve image segmentation per pixel, the overall characteristics obtained at the bottleneck layer must be oversampled to the ground truth image with decoder. At final, softmax classifier received decoder result and produce final output.

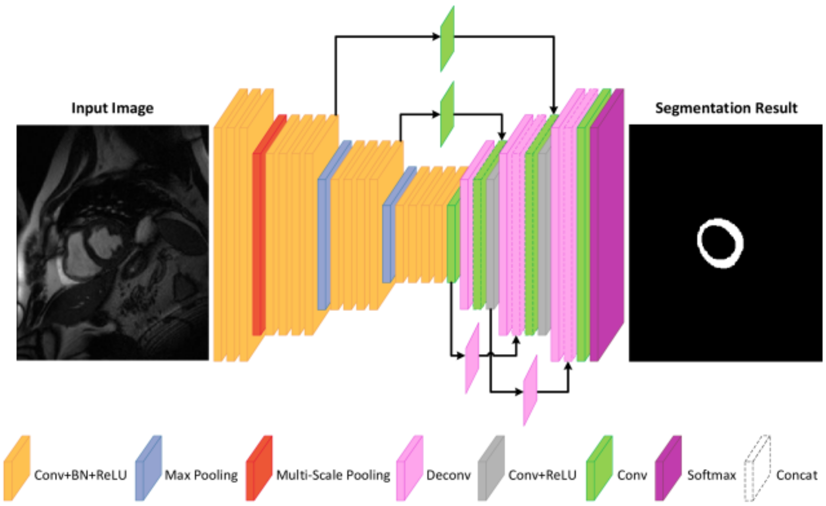

Fig.1: A typical FCN architecture for MRI Image Segmentation[16]

2.3.U-Net

The other FCN network, U-Net [6] which is also made with the combination of an encoder and decode. The encoder is used to retrieve set of characteristic from ground truth image and then next decoder is used to restore set of characteristicto its equivalent image and the overall structure is described in figure 2. However, it is observed that at the stage of encoder continuously the characteristics of features are reduced and size of features to be decreased. Later in the decoder stage features are generated.

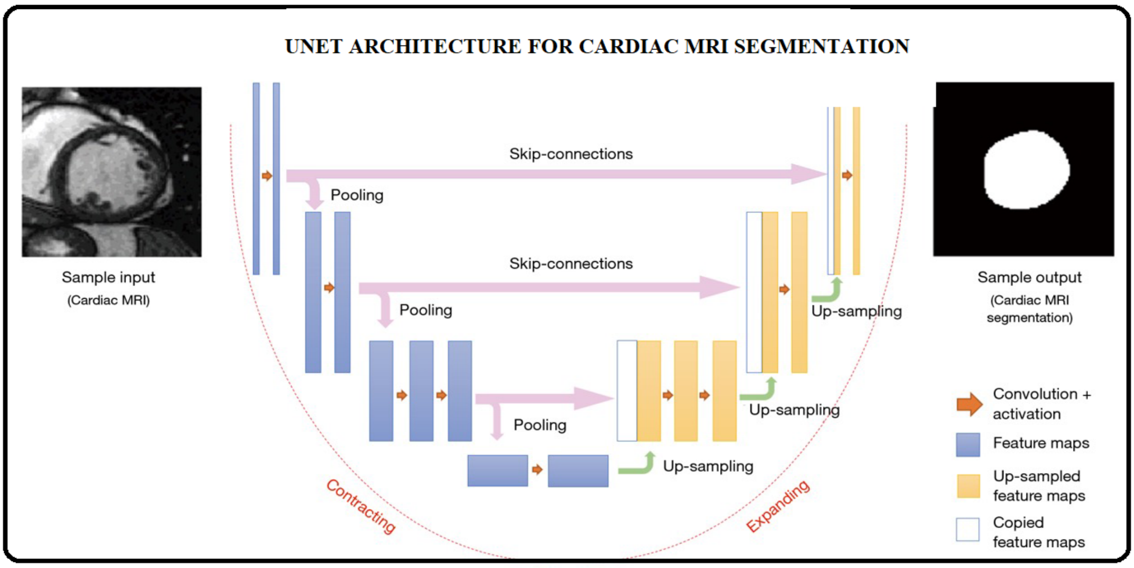

Fig.2: A typical UNET architecture for MRI Image Segmentation

Moreover, U-Net to reduce the loss function in ground truth image by connecting layers with both the blocks i.e., encoder and decoder.The limitation of U-Net is it has only one set of convolution block related to map functionality and it has equal size for both encoder and decoder.Also, it is mentioned that this network is structurally generate set of concatenated layers with that end part of the encoder is connected to the low level of the encoder and similarly the beginning of the encoder is connected by the high level of functions.

3. PROPOSED WORK

The work in this paper, introduced proposed method with composition of fourdifferent tasks: i) preprocessing ii) ROI Extraction iii) Model Learning with T-SegNetHybrid architecture forclassification and iv) Proposed Optimization for segmentation of LV images. The complete idea of the proposed method described in Figure 3.

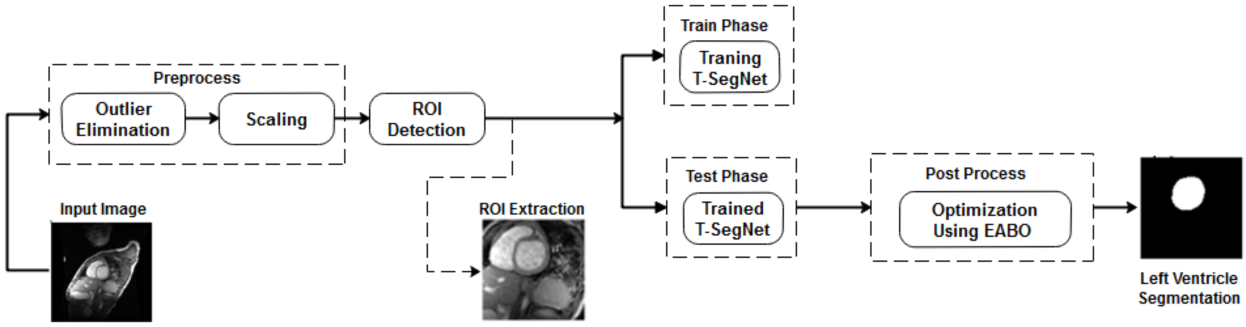

Fig 3: Global functional diagram of the proposed algorithm.

3.1. Preprocessing

Generally the MRI images are made with noise due to in proper acquisition process and result high end pixel and shows clearly in the respective image histograms. The initial task of any cardiac image segmentation is to reduce such kind of noises and modified with intensity values which are very near to the neighbor pixels. However, the resultant image after noise elimination results image with different intensity values and it can be resolve with the method of normalization. After, normalization resultant image to be the range of between 0 and 1 and this can be passed as input to be desired fully convolution network.

3.2. Method of ROI (Region of Interest)

The method of detecting the ROI is done with a series of steps which includes the estimation of the absolute difference among the each of the two successive blocks, the sum of all absolute differences.Next, performed method of Threshold to extract the relevant protruding part.At last, the bounding box of ROI is extracted.

3.3. Hybrid T-SegNet for image classification

The performance of basic neural networks is improved by using different techniques among multi task based approaches are prominent. In this article, we focus on the HTL(Hybrid Task Learning)network in which the original T-Net architecture is combined with SegNet to perform both the skip connections as well as the pooling indices for oversampling. Basic criteria ofT-Net is organizes grouping and oversampling accordingly in the process of encoding and decoding as result will get same size of features in single channel. Also, observe that,functionalities are represented at the start of the decoder which are retrieved from low level to the high level. The complete architecture of T-Net is illustrated in Figure 4.

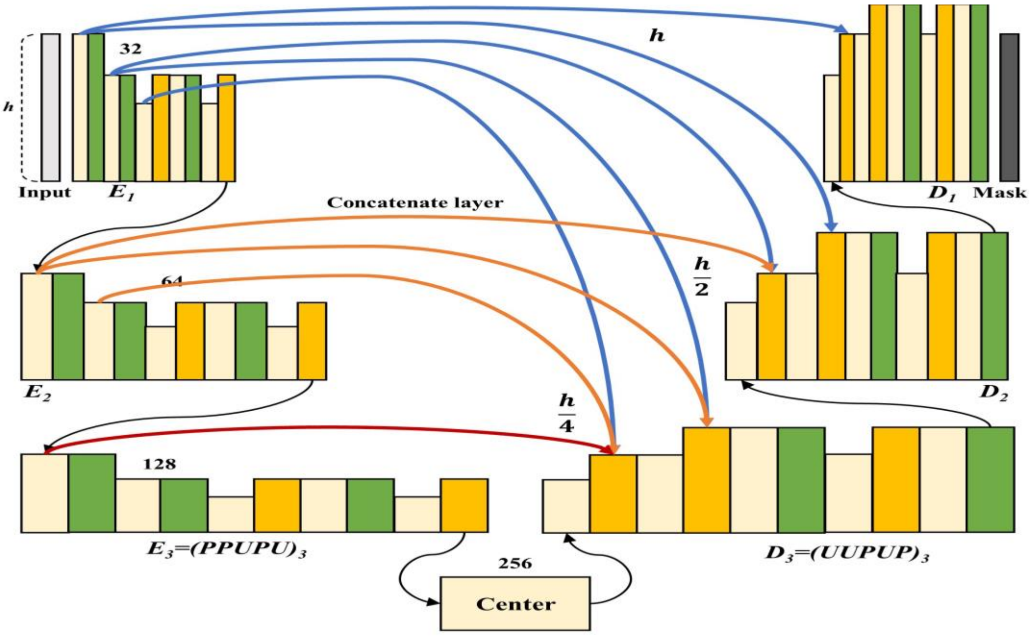

Fig.4: A Typical T-Net Architecture

In a SegNet architecture, the location of feature maps during subsampling (i.e., grouping indices) is recorded during coding, so that the decoder produces sparse feature maps in sampling its inputs using these pooling indices. These sparse feature maps are then convoluted with trainable filters to obtain feature maps, and are ultimately passed through a soft max classifier to produce image segmentation by pixel. Since the decoder in the SegNet architecture only uses the overall functionality obtained at the coder bottleneck layer, the high frequency details of the segmentation are lost during the process of sampling.We have observed that the deconvolution filters learned in the original T-Net architecture can be replaced by a SegNet type decoder to form a hybrid architecture with reduced network parameters. We call this modified architecture the T-Seg-Net shown in Figure 5.

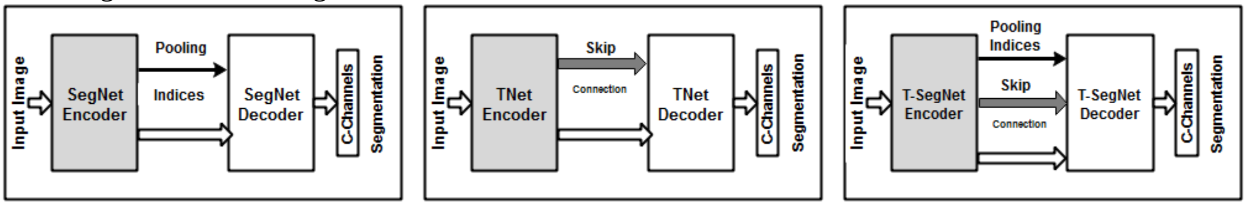

Fig 5. (a) SegNet architecture, (b) TNet architecture, and (c) T-SegNet architecture, using the two jump connections as well as the grouping indices for oversampling.

3.4. EXTENDED OPTIMIZATION OF THE AFRICAN BUFFALO

The African buffalo optimization[11-15] algorithm essentially models the three main characteristics mentioned above of the African buffalo. The "maaa" sound of the buffalo $k=(1,2,.....,n)$ is represented by m_k the sound "waaa" is represented by w_k. The same equation (2) is used to identify the location of the diseases.

$$m_{k+1} = m_k + LP_1(bg_{\max} - w_k) + LP_2(bp_{\max.k} - w_k) \quad (2)$$

Or, m_k indicates the current position of diseases $k=(1,2,.....,n)$, $bg_{\max}$ represented as the location of the most affected cardiovascular diseases and $bp_{\max.k}$ indicates the location of all cardiovascular disease and the parameters are $LP_1, LP_2 \in [0,1]$.

African Buffalo Optimization for Cardiac MRI Segmentation

1. Identify the location of diseases using the equation. (2)

$$m_{k+1} = m_k + LP_1(bg_{\max} - w_k) + LP_2(bp_{\max.k} - w_k)$$

2. Update the location of the disease using (3)

$$m_{k+1} = \frac{w_k + m_k}{\psi}$$

or, w_k refers to cardiovascular disease and ψ designates the affected party.

3. Is $bg_{\max}$ update. Yes, go to 4. No, go to 1
4. If the stop criteria are not met, return to step 1 of the algorithm, otherwise go to step 5
5. Generate the best solution**.**

Although the ABO algorithm has outperformed the reference functions in, but has certain limits. Two limitations of the ABO algorithm are resolved with modifications:
In order to introduce the democratic behavior of the herd, the buffalo population is sorted according to their fitness values and then divided into two groups. The upper half of the population will be considered the leading group of the herd. These leaders will follow the main herd leader, namely bgmax, known as the "pathfinder". Likewise, a buffalo from the bottom half of the population will follow its adjacent or local leader. The Community legislator will be chosen at random from the parliamentary group of the upper half of the population.
Reset under parliamentary feature will provide advice to poor buffaloes to head towards their strong leaders.

ExtendedAfrican Buffalo Optimization for Cardiac MRI Segmentation

1. Identify the location of diseases using the equation.

$$m_{k+1} = m_k + LP_1(bg_{\max} - w_k) + LP_2(bp_{\max.k} - w_k)$$

Or, m_k indicates the current position of diseases $k = (1, 2, ..., n)$, $bg_{\max}$ represented as the location of the most affected cardiovascular diseases and $bp_{\max.k}$ indicates the location of all cardiovascular disease and the parameters are $LP_1, LP_2 \in [0,1]$.

2.Sort the locations of the diseases according to their intensity values.

3.Update the location of the disease with i; where i = [sortedupper part of the disease, $i = 1, 2, 3, ..., {}^{np}\!/_{2}$ using (2) and (3)

$$m_{k+1} = \frac{w_k + m_k}{\psi}$$

4. generate a random number, $r_1 = [0,1]$

I) Yes $r_1 \geq 0.5$ then update the intensity of the disease location k, from the bottom half of the disease, as suggested below

$$m_{k+1} = m_k + LP_1(bg_{\max} - w_r) + LP_2(bp_{\max.k} - w_r)$$

or r is the location chosen at random in the upper half of the disease $r = \{i = 1, 2, 3, ..., {}^{np}\!/_{2}\}$, called local legislator.

The modification suggested in (4) will help the group of locations in the upper half to guide their classmates in the picture of the disease in the lower half.

ii) Update the position of the disease j^{th}, as follows

$$w_{k+1} = \frac{w_k + m_k}{\psi}$$, k = $k = ({}^{np}\!/_{2} + 1), ..., np$

iii)Yes $r_1 < 0.5$ then randomly update the location of the location of disease j, as suggested below

$$w_{k+1} = b_{\min} + (b_{\max} - b_{\min}) * r_2$$

or, $b_{\min}$, $b_{\max}$, and $r_2 = [0,1]$ are the minimum and maximum authorized localization limits of the disease, and the random number respectively.

5. Repeat steps 1 to 4 until the stop criteria are met.

Thus, the T-SeqNet approach proposed with EABO segments the LV MRI images of Cardiacdisease. The results of the implementation provide the effectiveness of the proposed method.

4. Experimental Results

The proposed model is implemented using MATLAB R2018b. The T-SegNet proposed with the EABO algorithm is used to segment the LV MRI images ofCardiac disease.

4.1. Datasets

The images were acquired from the Cardiac MR Group at Skåne University Hospital. On the images of systolic end and diastolic end, delimitations were made by experts of the MR heart group. In total, a dataset of 6,973 images was used. The dataset has been divided into systolic and diastolic end images, we call the two datasets systolic and diastolic datasets. A dataset consisting of these two datasets was also used, we call this dataset the merged dataset.

4.2. Evaluation and Metrics

Performance was assessed by segmenting the test set and comparing it to the ground truth. Three measurements were calculated, the precision, the dice score, the sensitivity, the Jaccard index of the classification of cardiac pixels LV. All these elements are defined respectively in (3) to (6).

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{3}$$

$$Dice = \frac{2TP}{2TP + FP + FN} \tag{4}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{5}$$

$$Jaccard_{Index} = \frac{TP}{TP + FN + FP} \tag{6}$$

The systolic and diastolic datasets were randomized to 80% training data and 20% tests, and the merged dataset used the same training and test data as the other two, but combined. Table 1 presents the results of the network assessment. The hybrid network works better than T-Net and Seg-Net on separate datasets and the merged dataset.

Table 1: Measured performances of the hybrid networks formed on the systolic, the diastolic and merged datasets. Training package: 80% and test package: 20%.

Database	Network	Accuracy	Dice	Sensitivity	Jaccard Index
Systolic	T-Net	0.975	0.798	0.7777	0.7777
	SegNet	0.955	0.818	0.7972	0.7972
	Merged	0.975	0.878	0.8572	0.8572
Diastolic	T-Net	0.965	0.748	0.7272	0.7272
	SegNet	0.945	0.798	0.7777	0.7777
	Merged	0.975	0.858	0.8372	0.8372
Merged	T-Net	0.955	0.768	0.7472	0.7472
	SegNet	0.935	0.828	0.8072	0.8072
	Merged	0.975	0.888	0.8672	0.8072

The same training was done using a smaller training set, where 8% of the data set was used for training and 92% was used for testing. Table 2 shows the results of the assessment using the small data sets. Using a smaller drive assembly results in a significant drop in performance, as expected. The results confirm the superiority of the merged network compared to the other two.

Table 2: Measured performances of the hybrid networks formed on the systolic, the diastolic and merged datasets. Training package: 8% and test package: 92%

Database	Network	Accuracy	Dice	Sensitivity	Jaccard Index
Systolic	T-Net	0.92625	0.7581	0.73834	0.73834
	SegNet	0.90725	0.7777	0.75734	0.75734
	Merged	0.92625	0.8341	0.81434	0.81434
Diastolic	T-Net	0.91675	0.7106	0.69084	0.69084
	SegNet	0.89755	0.7581	0.73834	0.73834
	Merged	0.92625	0.8151	0.79534	0.79534
Merged	T-Net	0.90725	0.7296	0.70984	0.70984
	SegNet	0.88255	0.7866	0.76684	0.76684
	Merged	0.92625	0.8436	0.82384	0.76684

The complexity of the model and the average time required to perform both training and testing tasks of the models mentioned in the Table 3.

Table 3: Model complexity, Hybrid Network and Standard Network learning computation time.

Models	Train time (min /epoch)			Test time (ms /volume)		
	Systolic	Diastolic	Merged	Systolic	Diastolic	Merged
A T	2.37	14.16	17.94	72	74	83
T-Net	2.29	13.77	17.43	77	64	81
SegNet	2.52	14.73	18.68	78	65	82
T-SegNet	4.60	18.08	23.54	89	72	91

Image segmentation is a necessary process in the medical image processing that is used to observe disease information. Heart disease is classified using the hybrid network approach called T-SegNet and finally, Affected parts are segmented using the extended African buffalo optimization technique and the results shown in Figure 6.

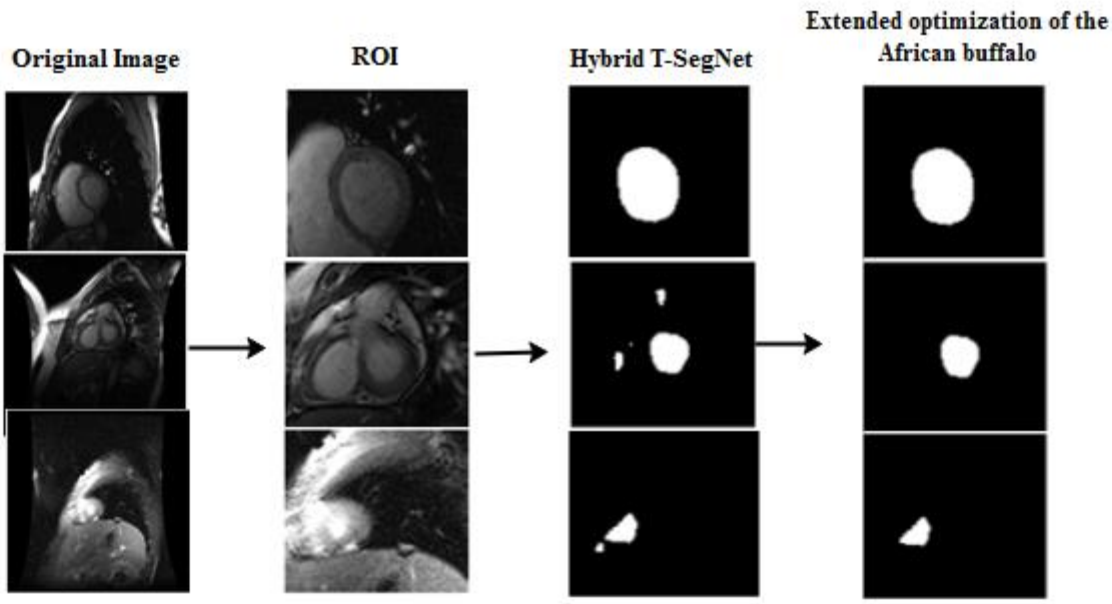

Fig 6: Results of the Proposed Method

In the end, we also compared the proposed results with other optimized algorithms called ACO techniques (Ant Colony Optimization) and (ABO) African Buffalo Optimization.

Table 4: Comparison for different segmentation techniques

Techniques	Precision	Sensitivity	Specificity
CO	96.04	79.38	70.56
ABO	96.31	87.02	90.94
EABO	98.68	96.14	95.97

The evaluation of existing methods and our proposed technique is explained in the Table. 4. The sensitivity values of the existing approaches are 79.38%, 87.02% and the proposed method achieves a high sensitivity of 96.14%. The proposed approach also gives a better specificity of 95.07% compared to the other methods. The overall accuracy of the archives of the proposed methods is almost 99% compared to existing methods.

5. CONCLUSION

The work in this paper, proposed LR based MR cardiac image segmentation using hybrid neural networkand extended optimization techniques. To implement the proposed neural network method, we added a T-Net with Seg-Net to perform both the pooling and the sampling task simultaneously.In this article, we have proposed a method of segmenting the left ventricle in Cardiac MRI images. Our proposed segmentation method includes three main steps. In the first step, we extract the region of interest using the movement of the heart in the frames of a cycle with normalization and noise elimination. In the second step, we used a hybrid convolutional network for classification and the last step is to segment the candidate regions using the EABO method. We applied our proposed method on a publicly available dataset and achieved 99% accuracy.

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