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# Android Application for Detection and Localization of Epicardial Fat using Morphological Filters

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**Abstract :** Today cardiovascular disease is the leading cause of death in the world wide. More than 62 million Americans have some form of cardiovascular disease. Together they resulted in 17.3 million deaths (31.5%) in 2013 up from 12.3 million (25.8%) in 1990. The socio-economic impact is considerable it has been predicted that approximately 23.6 million people will die from CVD in 2030. In existing method various techniques used to detect the cardiovascular disease are echocardiogram, cardiac stress test, CT and MRI scans. These are used but the produced images are less information and cardiologist spend more time to predict and to make the decision.The cardiac fats are correlated to several cardiovascular risk factors. The quantifying of fat couldn't be found out manually, therefore the different type of image processing technique will be applied to the low resolution image. In this paper, the quality of the image is pre-processed by using FCM algorithm and get a high resolution image is segmented, the PCA feature with BPNN and FIS classifier gives the better accuracy in classifying normal and abnormal conditions of the epicardial, then the image is given to the PIC microcontroller, with the help of Bluetooth driver the information will be displayed on the LCD. And also the images are displayed on the doctor's mobile phone with the help of mobile apps by using Wi-Fi connection.

**Keywords :** CT-Computed Tomography, PCA-pricipal Component Analysis, BPNN-Back Propagation Neural Network and FIS-Fuzzy Inference System Classifier, Epicardial Fat

## I. Introduction

Nowadays the most people face cardiac diseasesas a major problem in their life, because cardiovascular disease (CVD) is still the leading cause of death worldwide. There are various heart problems in medical domain but the most common problems are atherosclerosis, endothelial dysfunction, atherosclerosis plaque, stenosis and ischemia. A report by the World Health Organization (WHO) published in September 2011.The percentage of premature deaths from CVD ranges from 4% to 42% in high-and low-income countries respectively. More than 17.3 million people died from CVDs in 2008, representing 30% of all global deaths. Over 80% of CVD deaths take place in low- and middle-income countries. The socio-economic impact is considerable it has been predicted that approximately 23.6 million people will die from CVDs in 2030.

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**1.1 Epicardial fat**:

Epicardial fat is the adipose tissue accumulated between the visceral pericardium and the myocardium, without a structure or fascia separating it from the myocardium and the Epicardial vessels. EF has a variable distribution, being more prominent in the atrioventricular and interventricular grooves and right ventricular lateral wall.

There are various methods used to diagnosis this type of diseases like echocardiogram, cardiac stress test CT scan and MRI scan. By using this type of methodology, it gives lot of drawbacks for example by using echocardiogram it produce less information so cardiologist spend more time to predict the correct output and this equipments are produce noisy and more error signal will be added by this reason we go for another methodology.

Recent evidence also indicates that pericardial fat may be a significant cardiovascular risk factor; the reported result pericardial fat is highly correlated with visceral fat, suggesting that increased pericardial fat, like increased abdominal visceral fat, may be a significant index of risk for CVD.

**1.2 Epicardial Fat Thickness by CT:**

EF thickness can be measured in the right ventricular free wall and around the main coronary arteries the latter limited by the slice thickness, usually higher in tests assessing coronary calcium score. Fat thickness can also be measured in different regions of the heart surface, such as the right ventricular free wall and atrioventricular grooves.

**1.3 Epicardial Fat Volume at CT:**

This technique requires an adequate tool at the workstation to determine the volume of fat. The chest area where EF is visualized must be delimited by the operator, including slices 1 cm above the emergence of the left main coronary artery to the cardiac apex. The mean EF volume was 110 ± 41 mL in women and 137 ± 53 mL in men.

The steps are followed by the CT and MRI scans are:

a. Estimate object-specific (fat, non-fat, background classes) distributions using a training data set.

b. Remove artifacts and find the contour outline of the human body.

c. Segment and label various organs/tissues in cardiac scan.

d. Compute the fat statistics using the sample area around the seed point.

e. Compute the fuzzy affinity-based object.

When images present low count values, one cannot obtain reliable results. The same difficulty may be encountered when images are of lower quality.More patient images are necessary to show the robustness of the proposed method. Since the thresholding process is achieved manually by the clinicians, this may lead to little differences in the calculation of the percentage of abnormalities in artery vein

To overcome this problem, we introduced a new telediagnosis technology through this technique the doctor can easily identify the diseases with the help of Smartphone. By using this method the resultant image will be very accurate and without any errors. Additionally it transfers the information of the diseases.

Here we use software as well as hardware components first the input image (Dicom image) is given to the MATLAB. It also has some tool boxes useful for signal processing, image processing, optimization, etc. The pre-processing steps include de-noising and enhancement of an image after the completion of those steps then the enhanced image is fed to the segmentation process. It is process of each and every pixel can be segmented out by using FCM algorithm then segmented image is going to classified by BPNN classifier.

Those processes are done, and then the output is transferred to the PIC microcontroller this device is done by the analysis part and the information is displayed on the LCD with help of Bluetooth driver. The doctors can able to see the output image easily with the help of mobile apps. This technology will also helpful for the patients can easily see their normal and abnormal conditions using mobile apps, through this they are easily identify and analysis their severity level and also consulting with doctors immediately and take the action regarding to the diseases. By this methodology the time required to solve those problems are very less. And also it produces the more reliable result than compared to the other methods.

## II. Review of Related Works

Cardiac CT scan usually details only a small FOV strictly around the heart, although almost the entire chest is irradiated during image acquisition. A larger FOV is then available from the unprocessed data to examine the neighboring structures, such as lungs, breasts, Mediastinal, spine, and upper abdomen, with no additional X-rays exposure. While examining the entire FOV of a cardiac CT, it is frequent to encounter cardiac or extra-cardiac collateral findings (CFs) during the imaging study . The term “collateral finding” reflects an incidentally discovered mass or lesion, detected by CT, MRI, or other imaging modality, which is not related to the primary objectives of the examination; CFs are also called “incidental findings” or “incidentalomas”. A collateral finding is considered “clinically significant” when its detection warrants further investigations or therapeutic measures, or causes a change in the patient management. Most encountered extra-cardiac CFs pertain to the lungs, particularly small (<4 mm) pulmonary nodules. Other frequently met CFs are degenerative spine disease, aortic disease, swollen mediastinal or hilar lymph nodes, liver lesions. On this basis, several working groups reported about the prevalence and clinical significance of such CFs during cardiac CT scans. The early reports mostly referred to CT studies performed in order to diagnose coronary artery disease, which is the main indication for cardiac CT scan. The reported prevalence of CFs during 4 electron beam CT studies ranged between 7.8% to 53%, with 4.2% to 11% of scanned patients needing follow-up examinations; this wide range of prevalence can be explained by different technologies and definition of CFs used in those studies[26-29]. Along with the expanding indications for AF catheter ablation, there has been a parallel growth in the request of cardiac CT to depict LA and PV anatomy for image integration. As a consequence, some studies reporting CFs detected before AF ablation have been published.

Wissner *et al* studied 95 patients undergoing PV isolation between 2003 and 2007 with a 16-slice and subsequently 64-slice multidetector scanner, covering an area from above the clavicle to diaphragm, and found that 53% of patients had either cardiac or extracardiac CFs. Most CFs were extracardiac (78 out of 83), and more than half (46 out of 83) were pulmonary. Fifteen patients (16%) needed additional tests, and 6 of them (6.8%) had therapeutic implications due to the detection of unexpected findings. One patient (1.1%) had an adenocarcinoma of the lung diagnosed, which was treated surgically.

Sohns *et al* performed 64-slice multidetector CT of the chest and upper abdomen in 158 patients for identification of PV anatomy. They looked for extracardiac CFs only. A total of 198 extracardiac CFs were detected in 72% of patients, and 31% of patients had at least one clinically significant or potentially significant finding. Lung cancer was diagnosed in 2 patients (1.3%).

The same group assessed the incidence of both cardiac and extracardiac CFs among an extended population of 224 AF patients. In 91% of patients an average of 3.2 cardiac findings per patient were discovered, while 619 extra-cardiac findings (2.8 per patient) were detected in 80% of patients; Thirty-two percent of the 619 extracardiac findings were classified as “clinically significant”, including 2 cases of previously unknown cancers (esophageal and pulmonary, respectively; 0.9% of patients) and a newly diagnosed aortic dissection. The authors explained the relatively high incidence of extra-cardiac findings with the detailed image and the advanced age of their patients.

Schietinger *et al* reached analogous conclusions, finding extra-cardiac CFs in 69% of patients, the majority being pulmonary, and clinically significant CFs in 24% of patients at ECG-gated multidetector CT for PV evaluation.

Martins *et al* described a lower prevalence of CFs among 250 consecutive patients (23%). Half of the 76 CFs were pulmonary, including 2 lung cancers (0.8% of patients) and 2 pulmonary fibroses. Several findings led to specific disease management, but no focused follow-up was performed in order to get information about the impact of reviewing the entire FOV on patients’ outcome.

In summary, the proportion of patients with CFs is very high among the reported studies of cardiac CT performed for AF catheter ablation. Incidental findings requiring further investigations or follow-up are also quite frequent. Rather consistently, almost half of all collateral findings are represented by pulmonary nodules. Malignancy is diagnosed in a percentage ranging from 0% to 1.7% of patients.

Once a CF is reported, there is also uncertainty about the decision to follow up such findings over time. Some CFs are promptly deemed insignificant, that is, they do not require any additional examination. The dilemma about CFs follow up arises when so-called “clinically significant collateral findings” are detected. While the anxiety for medico-legal implications from underreporting incidental findings would lead to describe and follow up any lesion that is found in the FOV, some concern has been raised about increased financial burden in front of an unclear benefit while pursuing this strategy.

American guidelines on coronary artery imaging recommend a systematical review of extracardiac structures within the FOV during a CT scan, especially when risk factors for cancer exist. Missing a malignant cancer, especially in a potentially curable stage, would have deleterious consequences for the patient, as well as potential medico-legal implications for the radiologist. The Fleischner Society and the American College of Radiology provided some recommendations about how to manage incidentally detected small pulmonary nodulesand abdominal incidentalomas.

The Early Lung Cancer Action Project evaluated 1000 asymptomatic smokers aged at least 60 years, finding pulmonary nodules in 23% of the patients; twelve percent of these patients with noncalcified pulmonary nodules had lung malignancies, which were mostly non detectable on chest radiography[42].

Nevertheless, it is still unclear whether the strategy of examining the entire FOV and reporting all CFs would be beneficial for the patients' clinical outcome. In fact, reporting all CFs translates into additional follow-up with potential further radiation exposure, increased costs and patients' anxiety, and sometimes, invasive procedures are needed in order to complete the follow-up. Most of those CFs are eventually found to be benign and have little or no clinical influence on patients' health. A large study provided a cost analysis of following up such findings after CT scan for the screening of coronary heart disease[37]. Among 966 patients, 41.5% had extracardiac CFs. Additional diagnostic examinations required extra costs of 83.035 United States dollars. The authors concluded that reporting CFs did not provide a clear mortality benefit because CFs were not an independent predictor of noncardiac death. However, the authors did not report whether patients with a diagnosis of malignancy received life-saving or life-prolonging interventions, therefore it is not advisable to draw conclusions about difference in mortality between patients with and without CFs. Moreover, they used a too short mean follow up (18 mo) to evaluate the course of potentially slow-progressing diseases. Sohns *et al* estimated additional costs as high as about 42.543 United States dollars (190 United States dollars per patient) for subsequent diagnostic examinations (excluding invasive procedures) of incidentally detected extra-cardiac findings at cardiac CT before AF ablation. A clear clinical benefit was achieved in 1.1% of patients, however the authors did not attempt to investigate the potential clinical implications of such strategy.

In our opinion, on the basis of the potential detection of early stage cancers, until large studies analyze the cost-benefit ratio of such approach in a real-world scenario, the full set of abnormalities that are visible in the entire FOV should be reported, for ethical reasons. Obviously, once CFs are reported, smoking history, previous cancer, presence of first-degree relatives with history of cancer, or other known risk factors should be taken into account in the decision-making process of further follow-up.

## III. Proposed System

### 3.1 Denoise & Thresholding

A median filter operates over a window by selecting the median intensity in the window. Replace each pixel by the median over N pixels. It generalizes to "rank order" filters.

The Otsu threshold method changes an original image to a binary image. The simplest technique in the threshold method is to partition image into two regions based on threshold level. This threshold can be used to detect & differentiate the abnormal clusters.

### 3.2. Morphological operations (Opening and Closing)

The basic effect of an **opening** is somewhat like **erosion** in that it tends to remove some of the foreground (bright) pixels from the edges of regions of foreground pixels. As with other morphological operators, the exact operation is determined by a structuring element. The effect of the operator is to preserve *foreground* regions that have a similar shape to this structuring element, or that can completely contain the structuring element, while eliminating all other regions of foreground pixels. The opening operator therefore requires two inputs: an image to be opened, and a structuring element. **Closing** is opening performed in reverse. It is defined simply as dilation followed by erosion*using the same structuring element for both operations*. The closing operator therefore requires two inputs: an image to be closed and a structuring element. It tends to enlarge the boundaries of foreground (bright) regions in an image (and shrink background color holes in such regions).

### 3.3 Contrast Enhancement (CE)

The proposed technique is an adaptive histogram equalization technique that uses wavelet based gradient histograms. It gives good contrast enhancement, with better brightness preservationwithout losing edge information and with the minimum distortions to the enhanced images. By improving the image quality, we can detect the changes better than the conventional approach.

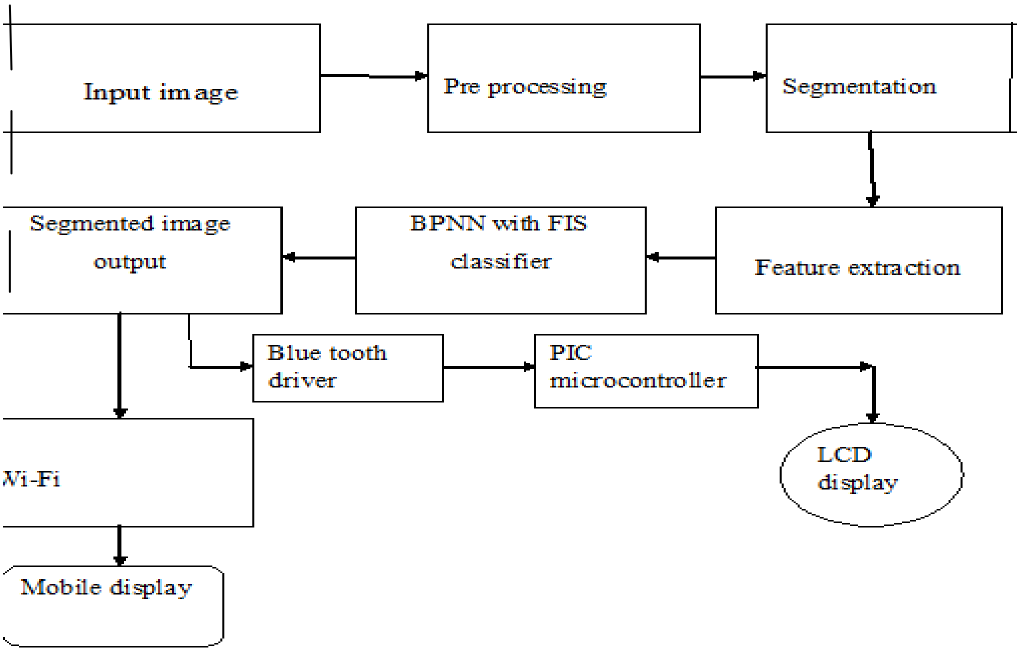


**Fig. 1 Methodology and Proposed work.**

### 3.4 DCT

First, the DCT is data independent. Second, the DCT can be implemented using a fast algorithm. The discrete cosine transform (DCT) represents an image as a sum of sinusoids of varying magnitudes and frequencies. The DCT has the property that, for a typical image, most of the visually significant information about the image is concentrated in just a few coefficients of the DCT. For this reason, the DCT is often used in image compression applications. For example, the DCT is at the heart of the international standard lossy image compression algorithm known as JPEG. The other one technique is Sobel Edge detection is the process of localizing pixel intensity transitions. The edge detection has been used by object recognition, target tracking, segmentation, and etc. Therefore, the edge detection is one of the most important parts of image processing.In this method, first, we have computed 2D-DCT of a word image. Let the 2D-DCT coefficient matrix of a image be D. Then, principal diagonal, upper $N - 2$ and lower $N - 2$ diagonals of D is extracted before and after flipping D, and further computed their standard deviations respectively as discussed in the aforementioned paragraph. Meanwhile, we have also extracted features based on conventional DCT. In this case, its coefficient matrix is divided into four zones and standard deviation of each zone is computed. Thus, a feature vector of four features is formed.

Wemust extract the features of the target image and compare it with all features vectors. Discrete cosine transform (DCT) is a powerful transform to extract proper features for face recognition. After applying DCT to the entire heart images, some of the coefficients are selected to construct feature vectors.

### 3.5 Feature Reduction – PCA

The method we imply for Dimensionality reduction is Principal Component Analysis (PCA). PCA works on the basis of projection, which observes real dimensions in the data. The unwanted dimensions can be cut down by performing a linear mapping of the data to a lower-dimensional space. The output will be the maximized variance of the data in the low-dimensional representation. Such a covariance matrix once when constructed, is followed by computation of the eigenvectors. The eigenvectors with higher eigenvalues can reconstruct a large fraction of the variance of the original data. Hence the original space gets reduced to the space spanned by a few eigenvectors.

The dimensional reduction of image is followed by sampling of image with respect to the resolution. We do quantization to compress the image with respect to its intensity. Quantization performs 'lossy compression' which makes a range of values to a single quantum value. The temporal and spatial resolution is also limited and we consider samples of the data to compress the image. The image is thus compressed by sampling.

### 3.6 FCM

We propose an FCM method to compute the weights for the neighbourhood of each pixel in the image. The proposed clustering method can not only overcome the effect of the noise effectively, but also prevent the edge from blurring.

***Fuzzy C-Means***

Fuzzy C-Means (FCM), proposed by Bezdek et al. (1984), is based on the iteration process to optimize the membership matrix and the cluster centers. The objective function of FCM is defined as follows:

$$J = \sum_{k=1}^{N} \sum_{j=1}^{C} u_{kj} \times \| X_k - V_j \| \rightarrow min .......(1)$$

$$\begin{cases} u_{kj} \in [0,1] \\ \sum_{j=1}^{C} u_{kj} = 1 \\ k = \overline{1,N}; j = \overline{1,C} \end{cases}$$

In Eqs.some terms are used as follows:

• m is fuzzier;
• C is the number of clusters;
• N is the number of data elements;
• r is the dimensionality of the data;

- $X_k \in R_r$ is the $k^{th}$ element of X = {X1, X2, . . . , XN}, which is the main part from the Otsu method;
- $V_j$ is the center of cluster j.

Use the Lagrange method, the cluster centers and the membership matrix are determined

In fuzzy clustering, the pre-defined membership matrix is often opted to be the additional information.

To address intensity inhomogeneity, the proposed algorithm introduces the global intensity into it.It combines the local and global intensity information into account to ensure the smoothness of the derived optimal bias field and improve the accuracy of the segmentations. It allows pixels that belong to numerous clusters with changeable degrees of membership.It may able to determine final segmentation results from the pattern in a reasonable processing manner.

### 3.7 BPNN

Among all classifiers, convolution neural network (CNN) with BPNN is one of the most promising solutions to meet the challenges of heart fatal detection by virtue of its high capability in extracting powerful high-level features. The deep CNNs, we propose the potential of using back propagation architectures with small convolution kernels for segmentation of fats in input images. Compared to conventional classifier, additional feature are extracted to test & train the classifier, which improves its robustness against intensity variation and changes in imaging sequences. It designs a deeper architecture, besides having a positive effect against over fitting, given the fewer number of weights in the network.

They are stacks of restricted Boltzmann machines forming deep (multi-layer) architecture. Insufficient depth may require more computational elements, than architectures whose depth is matches to the task. Deep Belief nets are composed of Restricted Boltzmann machines (RBM) which are energy based models.

### 3.8 FIS Approach

Fuzzy logic models, called fuzzy inference systems, consist of a number of conditional "if-then" rules. For the designer, these rules are easy to write, and as many rules as necessary can be supplied to describe the system adequately. We will analyze the differences between each pixel using a local operator.

The fuzzy logic approach can be implemented through a Fuzzy Inference System (FIS) that formulates the mapping from multiple inputs to a single output. It further improves target detection and localization accurately. The experimental results will show that the proposed fuzzy logic approach to pixel-wise change detection provides better outcome than the previous approach.

## IV. Result and Conclusion

### 4.1 Result

Fuzzy c-means clustering algorithm is executed to segment the high resolution image. Further is implemented to detect the AMOUNT OF FAT DEPOSITION in coronary artery.

**Output Images**

#### 4.1.1 Input Image

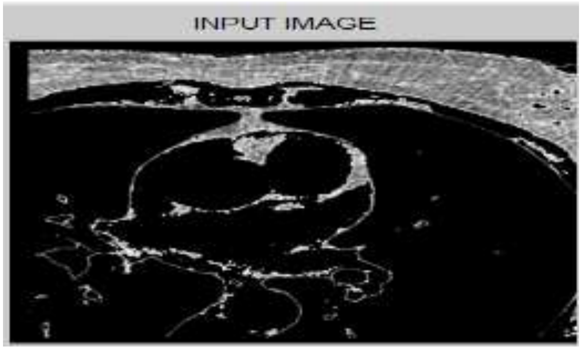


**Fig.2. Input image**

#### 4.1.2 SRAD Image

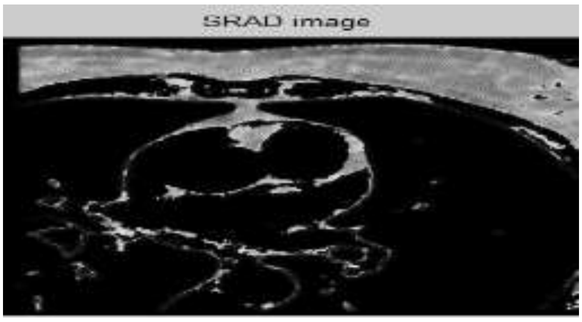


**Fig. 3 SRAD image**

### 4.1.3 Enhancement Image

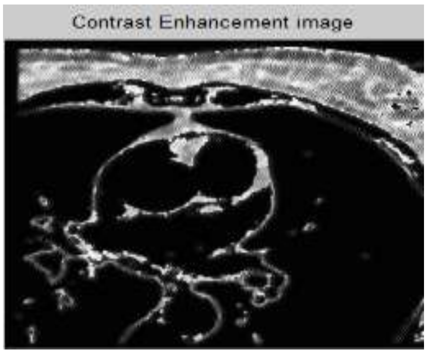


**Fig.4 Enhancement image**

### 4.1.4 Segmentation Image

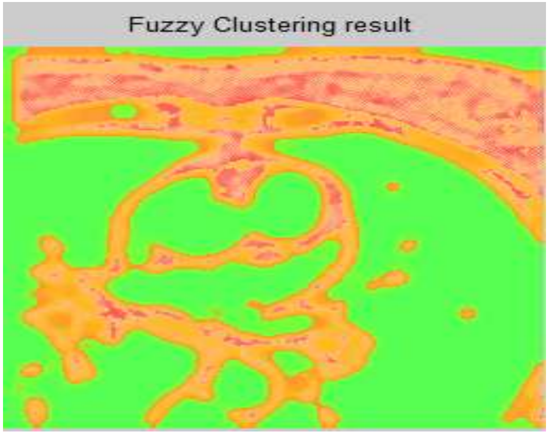


**Fig.5 Segmentation image**

### 4.1.5 Accuracy Graph Comparision

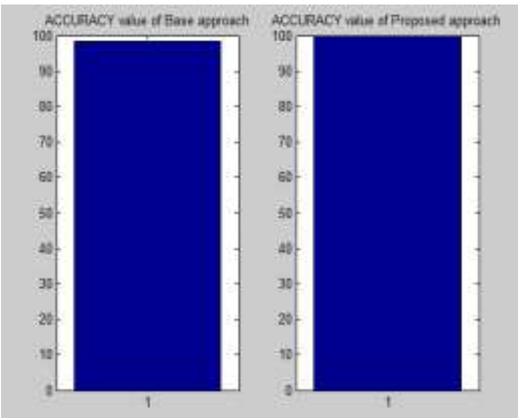


**Fig.6 Accuracy graph comparison**

## V Conclusion

This paper plays an important role in medical diagnostic purpose in medical environment. In this project, we improve the low resolution image as like high resolution image. By means of fuzzy c-means algorithm, the high resolution image is segmented, and then the blocked portions are detected and also the diagnostic accuracy is improved

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