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HEART BLOCK SEGMENTATION USING IMAGE PREPROCESSING

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ABSTRACT

Heart block diseases are one of the most deadly diseases with a high mortality rate. The shape and size of the block are random during the growth process. Heart Block segmentation is a heart block assisted diagnosis technology that separates different block structures such as edema and active and block necrosis tissues from normal heart tissue. Magnetic resonance imaging (MRI) technology has the advantages of no radiation impact on the human body, good imaging effect on structural tissues, and an ability to realize tomographic imaging of any orientation. Therefore, doctors often use MRI heart block images to analyze and process heart blocks. In these images, the block structure is only characterized by gray scale changes, and the developed images obtained by different equipment and different conditions may also be different. This makes it difficult for traditional image segmentation methods to deal well with the segmentation of heart block images. Considering that the traditional single-mode MRI heart block images contain incomplete heart block information, it is difficult to segment the single-mode heart block images to meet clinical needs. In this work, an automatic thresholding algorithm is introduced to process the diagnosis of MRI heart block images. In the absence of added noise, the proposed algorithm has better advantages than traditional methods. Experimental results show that the proposed algorithm has better noise immunity than a comparable algorithm.

1. INTRODUCTION

Coronary Artery Disease(CAD) is the important cause of human death in various countries all around the world. Every year millions of dollars is invested for treatment of coronary artery disease too, yet it possess a serious potential threat to millions of lives. Due to the existence of several heart imaging modalities the detection of cardiac blockage was made easy. Over last few years, several steps were taken in the area of cardiac imaging techniques. As result rapid improvement and development were made in this area .Presence of plaque in walls of coronary arteries are chief indicators of Coronary Artery Disease.

The five main coronary arteries are the main areas of plaque deposition are the Right Coronary artery (RCA), Posterior Descending (PDA), the Left Main (LM), Left Circumflex (LCX) and Left Anterior Descending (LAD). It can observed from medical reports that will be able to diagnose properly and hence can provide better and reliable treatments to the affected people if the cardiac disorders gets detected as early as possible. Due to presence of various improved and advanced noninvasive medical imaging methods, it become very easy for doctors and cardiologists to detect, diagnose, perform surgeries and operations. But still cardiac blockage is a severe problem among all other heart disorders. Accurate detection and diagnosis of blockage is required for proper cardiac treatment. Proper medication could be provided to the affected patients before its too late.

An arrhythmia is a problem with the rate of the heartbeat. During an arrhythmia, the heart can beat with irregular heartbeat. When a heart beats too fast is called tachycardia. When a heart beats too slowly is called bradycardia. It is caused by changes in heart tissue and activity or in the electrical signals that control heartbeat.

These changes can be caused by damage from disease, injury, or genetics. Often there are no symptoms, but some people feel an irregular heartbeat. It may feel faint or dizzy or have difficulty breathing.The most common test used to diagnose an arrhythmia is an electrocardiogram. If arrhythmia is left untreated, the heart may not be able to pump enough blood to body. This can damage the heart, the brain, or others.

2. LITERATURE REVIEW

Akhbardeh et al. presented categorization of the clogs in the arteries by applying the frames generated from the X-ray angiography. Performing image pre-processing methods includes selecting a line of Interest (on blocked artery and further selection of the region of interest on that area, then automatically cropping the region of interest followed by Gaussian filtering. The paper displayed three alternative methods are proposed to measure the stenosis in the vessel. The first method applies thresholding to extract the vessel of interest. The extracted vessel is analyzed for the calculation of the stenosis in percentage. The second method utilizes segmentation of the vessel tissue over the extracted pixels of ROI. The final method is based on using K-means clustering to differentiate between the vessel regions and non-vessel regions. Among the proposed methods K-means clustering based method outperforms better than others [1].

Supriya Agrawal in her paper proposes a method for automated segmentation of cardiac stenosis. Pre-processing is done for image analysis. Pre-processing includes image enhancement and pre-segmentation. Image enhancement is done to remove the noise removal and improves the visual quality. Segmentation of the arteries is done through Hessian based Frangi's vesselness filter. Abnormality in the segmented arteries is detected through Sobel Edge Gradient Operator along with the threshold values 76 to 80. This projects the edges which are the regions having high spatial frequency. The gradient magnitude is computed at each point for detecting the stenosis [2].

Shahzad R. and et.al [3] in his work described a method which consists of extracting centerlines with the help of already known start and end points of arteries. Then it detects bifurcation points and then the points and centerlines are divided into segments. This changes centerlines to segments. The next step is to initialize the centerline segments for segmenting the lumen. The segmentation of the lumen is done by combining robust kernel regression and graph-cuts.

Reiber J.H.C. and et all describes the methodology of such a computer-assisted analysis system, as well as the results from a validation study on the accuracy and precision. A region in a 35 mm cineframe encompassing a selected arterial segment is optically magnified and converted into video format by means of a specially constructed cinevideo converter and digitized for subsequent analysis by computer. Contours of the arterial segment are detected automatically on the basis of first and second derivative functions. Contour data are corrected for pincushion distortion; arterial dimensions are presented in mm, where the calibration factor is derived from a computer-processed segment of the contrast catheter. The accuracy and precision of the edge detection procedure as assessed from cinefilms of perspex models (%-D stenosis ≤ 70 percent) filled with contrast agent were -30 and 90 μ m, respectively. The variability of the analysis procedure by itself in terms of absolute arterial dimensions was less than 0.12 mm, and in terms of percentage arterial narrowing for coronary obstructions less than 2.74 percent. It is concluded that this system allows the measurement of coronary arterial dimensions in an objective and highly reproducible way [4].

The geodesic active region model presented by Nikos and et all [23], who integrates boundary-based with region-based active contour approaches, is more effective than region-based snake segmentation methods, because prior knowledge about ROI is introduced. The important problems in the region-based approaches include the design of region-based models. We have used Vessel Enhancement Diffusion filtering developed by Frangi to enhance/Segment the vessels/Coronary arteries [5].

Mazinani M. and et all proposed an algorithm in their report on a similar kind of research. In order to extract coronary arteries and measure the degree of stenosis, they used Markovian fuzzy clustering method is applied to model uncertainty arises from partial volume effect problem. The algorithm employs: segmentation, centerline extraction, estimation of orthogonal plane to centerline, measurement of the degree of stenosis. To evaluate the accuracy, their approach has been applied to a vascular phantom and the results are compared with real diameter. [6]

3. METHODOLOGY

This work has five main modules such as input image, pre processing, segmentation, feature extraction and classification.

MODULES DESCRIPTION

The proposed method is composed of four parts which are given below –

- **Image Input**
- **Pre-Processing**
 - **GRAY SCALE**
 - **NOISE FILTER**
 - **HISTOGRAM EQUALIZATION**
- **Segmentation**
 - **AUTOMATIC THRESHOLDING**
 - **CANNY EDGE DETECTION**

- **Feature Extraction**
 - GLCM
 - AREA
- **Classification**

2.2 INPUT IMAGE

In the first stage, as input image, one Toshiba CTA image and two CTA images of artery of heart have been acquired. After acquiring the image, nearest neighbor interpolation method were performed for image scaling.

Then, moving on to the pre-processing stage where we used Gaussian Soothing for reducing color complexity. Later Luminosity method were for grayscaling where blue color was prioritized while converting the images. Finally Median Filtering has been used to reduce noises.

2.3 PREPROCESSING

Image Processing Techniques Related to Coronary Artery Blockage Detection

2.4 GRAYSCALE IMAGE

An RGB image can be viewed as three images(a red scale image, a green scale image and a blue scale image) stacked on top of each other. In MATLAB, an RGB image is basically a $M*N*3$ array of colour pixel, where each colour pixel is a triplet which corresponds to red, blue and green colour component of RGB image at a specified spatial location.

Similarly, A Gray scale image can be viewed as a single layered image. In MATLAB, a gray scale image is basically $M*N$ array whose values have been scaled to represent intensities.

In MATLAB, there is a function called `rgb2gray()` is available to convert RGB image to gray scale image. Here we will convert an RGB image to gray scale image without using `rgb2gray()` function.

2.5 NOISE FILTER

2.5.1 Median Filter

Median filter is also used to reduce the amount of noise in an image. But it has two major advantages over mean filter. Firstly it gives more vigorous average of the pixels than mean filter. Secondly, it does not create unrealistic pixel value while filtering. Thus gives us sharper edges than mean filtered image [21]. Median filter also follows a simple working procedure. For every pixel in an image, its neighbor pixels are considered. First the neighboring pixels are sorted out and then the pixel is replaced by the median value of all the sorted pixels and if the neighboring pixels are even in number, then the average value of the middle two pixel value is used for the replacement [22].

An illustration of the calculation of median filtering is given below.

6	4	2
7	12	9
3	5	8

(a)

6	4	2
7	6	9
3	5	8

(b)

Fig. 2.4.1 (a) Matrix of pixel (b) Median Filtered matrix of pixels

Here, the center pixel value is 12. If the neighboring pixels are being sorted, then the sorted list will be as: 2, 3, 4, 5, 6, 7, 8, 9, and 12. The median value of the list is 6. Hence the center value(previously 12) will be replaced by 6.

2.5.2 Gaussian Smoothing Filter

The Gaussian smoothing operator is a 2-D convolution operator that uses a Gaussian function for calculating the transformation in each pixel. It is widely used to 'blur' images and also for removing noises and details from an image. The equations of Gaussian function in both 1D and 2D are given below:

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}} \quad (1)$$

$$G(x) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (2)$$

Here x is the distance from the origin in the horizontal axis, y is the distance from the origin in the vertical axis, and σ is the standard deviation of the Gaussian distribution.

Gaussian smoothing uses 2-D distribution function and when calculating new values of a given pixel, convolution operator is being used. Convolution takes values of the neighboring pixels into account. The main element of a convolution is kernel which is a matrix of arbitrary size mostly a square matrix. When calculating the new value of the selected pixel, the convolution kernel is applied to it by its center pixel. Neighboring pixels are covered with the same kernel. Next, the sum of the product of the pixels is calculated in the image. The resulting sum is the new value of the selected pixel. Now, if the convolution is applied to each pixel in the image, we get a certain effect, which depends on the chosen convolution kernel. An example of the calculation of Gaussian Smoothing is given below.

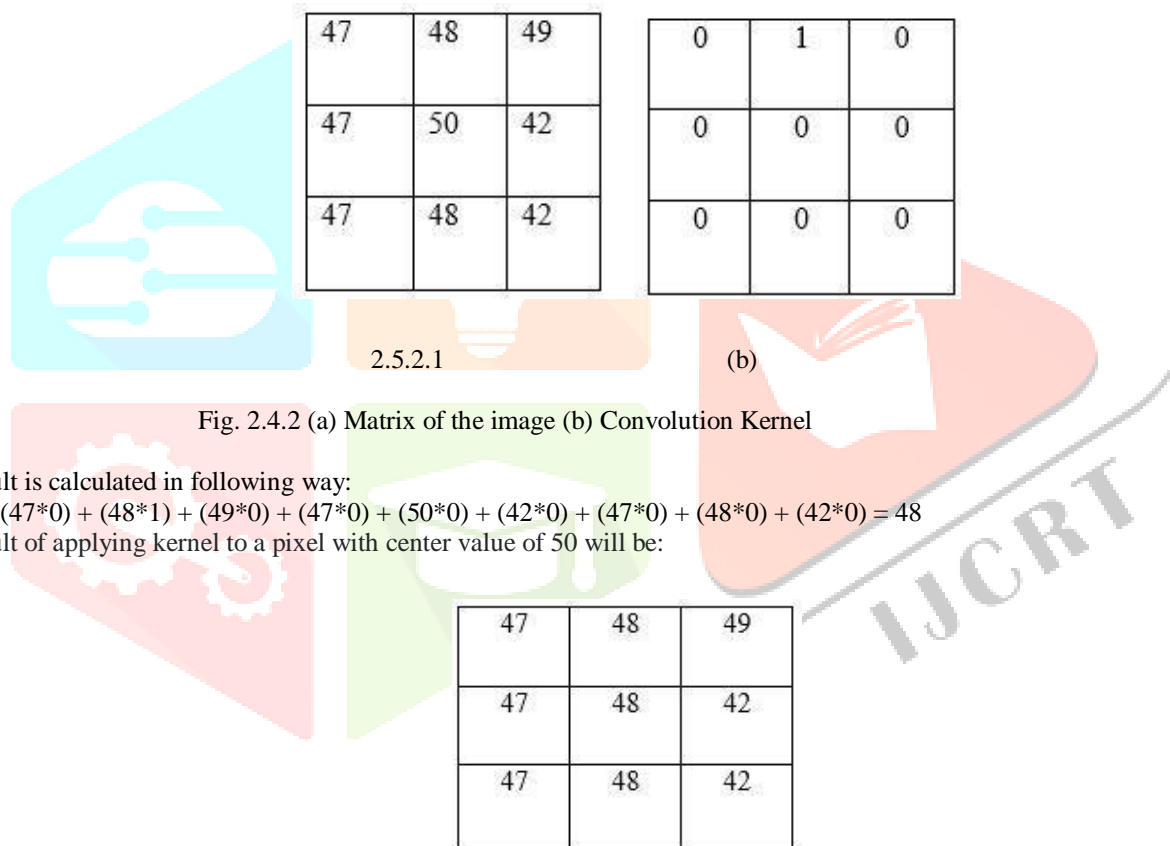


Fig. 2.4.2 (a) Matrix of the image (b) Convolution Kernel

The result is calculated in following way:

$$\text{Result} = (47*0) + (48*1) + (49*0) + (47*0) + (50*0) + (42*0) + (47*0) + (48*0) + (42*0) = 48$$

The result of applying kernel to a pixel with center value of 50 will be:

47	48	49
47	48	42
47	48	42

Fig. 2.4.2 Gaussian smoothing filtered matrix of the image

2.5.3 AUTOMATIC Threshold Algorithm

OTSU's algorithm is an image binarization algorithm named after its inventor Nobuyuki Otsu. This algorithm assumes that an image has two types of pixels (foreground pixels and background pixels), it then calculates the optimum threshold separating the two classes so that their combined spread is minimal, or equivalent, so that their inter-class variance is maximal [29]. In this method, a threshold value is searched that minimizes intra-class variance, defined as a weighted sum of variances of the two classes:

$$\sigma_{\omega}^2(t) = \omega_0(t)\sigma_0^2(t) + \omega_1(t)\sigma_1^2(t) \quad (3)$$

Weights ω_0 and ω_1 are the probabilities of the two classes separated by a threshold t and σ_0^2 and σ_1^2 are variances of these two classes. The class probability $\omega_{0,1}(t)$ is computed from the L bins of the histogram:

$$\omega_0(t) = \sum_{i=0}^{t-1} p(i) \quad (4)$$

$$\omega_1(t) = \sum_{i=t}^{L-1} p(i) \quad (5)$$

Otsu shows minimizing the intra-class variance and maximizing inter-class variance is equivalent.

$$\sigma_b^2(t) = \sigma^2 - \sigma_{\omega}^2(t) = \omega_0(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2$$

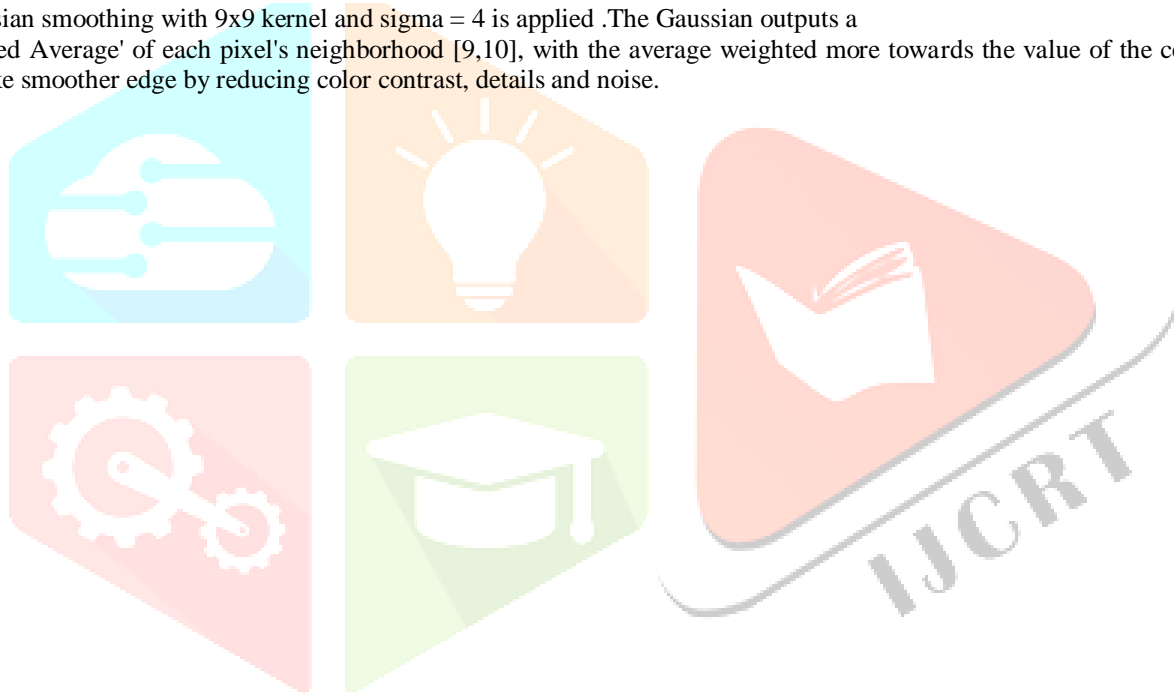
Pre-processing

The CTA images are needed to be pre-processed to reduce complexities in further process.

First

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2 + y^2}{2\sigma^2}}$$

of Gaussian smoothing with 9x9 kernel and sigma = 4 is applied .The Gaussian outputs a `Weighted Average' of each pixel's neighborhood [9,10], with the average weighted more towards the value of the central pixels . It will make smoother edge by reducing color contrast, details and noise.



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Furthermore, the images then converted into grayscale using luminosity method [11]. It averages the values, but it forms a weighted average to account for human perception. The images are more sensitive to red and blue than other colors, so red and blue are weighted most heavily. The formula for luminosity is:

$$\text{Gray} = 0.54 * R + 0.39 * G + 0.07 * B \quad (3)$$

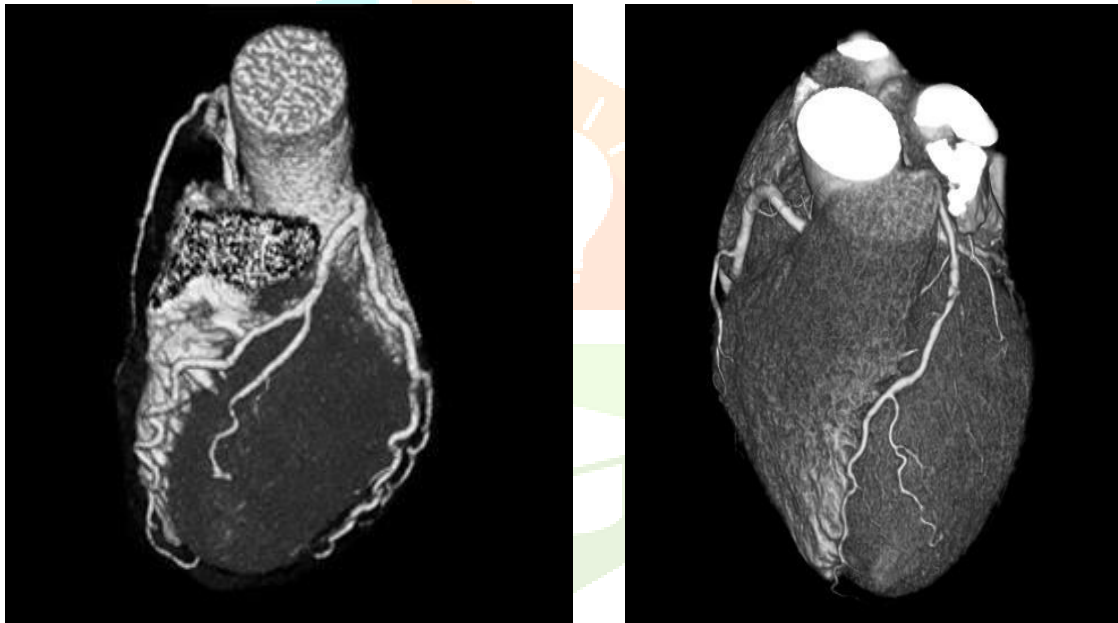


Fig. 6.3.2: Grayscale conversion using luminosity method.

Furthermore, to reduce noise median filtering has been used [12] gives vigorous average of the pixels. It is performed by the neighboring pixels that are sorted out and then the pixels are replaced by the median value of all the sorted pixels and if the neighboring pixels are even in number, then the average value of the middle two pixel value is used for the replacement.

2.6 Segmentation of Coronary Artery

In the coronary artery detection part, the system aims to detect the major parts or artery as block in the minor part doesn't fact a lot .Otsu Thresholding has been applied for thresholding. This algorithm assumes that an image has two types of pixels (foreground pixels and background pixels), it then calculates the optimum threshold separating the two classes so that their combined spread is minimal, or equivalent, so that their inter-class variance is maximal [13-15]. In this method, a threshold value is searched that minimizes intra-class variance, defined as a weighted sum of variances of the two classes:

$$\sigma_{\omega}^2(t) = \omega_0(t) \sigma_0^2(t) + \omega_1(t) \omega_1^2(t) \quad (4)$$

Weights ω_0 and ω_1 are the probabilities of the two classes separated by a threshold t and σ_0^2 and σ_1^2 are variances of these two classes. The class probability $\omega_0, 1(t)$ is computed from the L bins of the histogram:

$$\omega_0(t) = \sum_{i=0}^{t-1} p(i) \quad (5)$$

$$\omega_1(t) = \sum_{i=t}^{L-1} p(i) \quad (6)$$

2.7 CANNY EDGE DETECTION

The **Canny edge** detector is an **edge detection** operator that uses a multi-stage **algorithm** to **detect** a wide range of **edges** in images. It was developed by John F. **Canny** in 1986. **Canny** also produced a computational theory of **edge detection** explaining why the technique works.

Canny Edge Detection is a popular edge detection algorithm. It was developed by John F. Canny in

1. **It is a multi-stage algorithm and we will go through each stages.**
2. **Noise Reduction**

Since edge detection is susceptible to noise in the image, first step is to remove the noise in the image with a 5x5 Gaussian filter. We have already seen this in previous chapters.

3. **Finding Intensity Gradient of the Image**

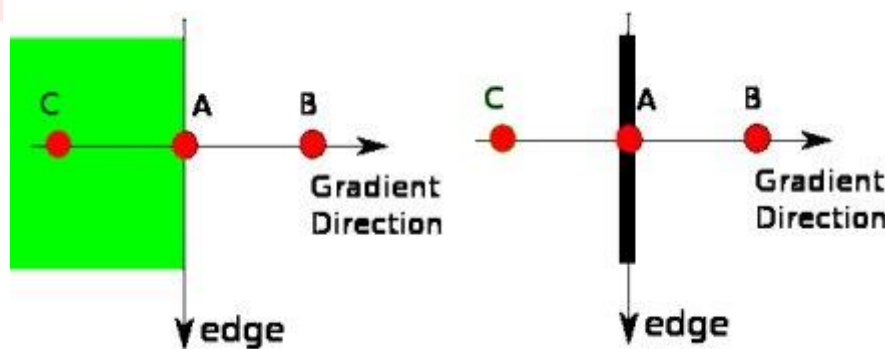
Smoothened image is then filtered with a Sobel kernel in both horizontal and vertical direction to get first derivative in horizontal direction (G_x) and vertical direction (G_y). From these two images, we can find edge gradient and direction for each pixel as follows:

$$\text{Edge_Gradient}(G) = \sqrt{G_x^2 + G_y^2} \quad \text{Angle}(\theta) = \tan^{-1}(G_y/G_x)$$

Gradient direction is always perpendicular to edges. It is rounded to one of four angles representing vertical, horizontal and two diagonal directions.

4. **Non-maximum Suppression**

After getting gradient magnitude and direction, a full scan of image is done to remove any unwanted pixels which may not constitute the edge. For this, at every pixel, pixel is checked if it is a local maximum in its neighborhood in the direction of gradient. Check the image below:



image

Point A is on the edge (in vertical direction). Gradient direction is normal to the edge. Point B and C are in gradient directions. So point A is checked with point B and C to see if it forms a local maximum. If so, it is considered for next stage, otherwise, it is suppressed (put to zero).

In short, the result you get is a binary image with "thin edges".

2.8 GRAY LEVEL COOCCURANCE MATRIX (GLCM)

GLCM is a second-order statistical texture analysis method. It examines the spatial relationship among pixels and defines how frequently a combination of pixels are present in an image in a given direction θ and distance d . Each image is quantized into 16 gray levels (0–15) and 4 GLCMs (M) each for $\theta = 0, 45, 90,$ and 135 degrees with $d = 1$ are obtained. From each GLCM, five features (Eq. 13.30–13.34) are extracted. Thus, there are 20 features for each image. Each feature is normalized to range between 0 to 1 before passing to the classifiers, and each classifier receives the same set of features.

$$\text{Energy} = \sqrt{\sum_{i,j=0}^{G-1} (M(i,j))^2}$$

$$\text{Homogeneity} = \sum_{i,j=0}^{G-1} \frac{M(i,j)}{1+(i+j)^2}$$

$$\text{Correlation} = \sum_{i,j=0}^{G-1} M(i,j) \left[\frac{(i-\bar{i})(j-\bar{j})}{\sqrt{(\sigma_i^2)(\sigma_j^2)}} \right]$$

$$\text{Energy} = \sum_{i,j=0}^{G-1} M(i,j) \times (i,j)^2 \triangle$$

$$\text{Entropy} = -\sum_{b=0}^{G-1} P(b) \log_2 \{P(b)\}$$

To create a GLCM, use the graycomatrix function. The graycomatrix function creates a gray-level co-occurrence matrix (GLCM) by calculating how often a pixel with the intensity (gray-level) value i occurs in a specific spatial relationship to a pixel with the value j . By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent), but you can specify other spatial relationships between the two pixels. Each element (i,j) in the resultant glcm is simply the sum of the number of times that the pixel with value i occurred in the specified spatial relationship to a pixel with value j in the input image.

Because the processing required to calculate a GLCM for the full dynamic range of an image is prohibitive, graycomatrix scales the input image. By default, graycomatrix uses scaling to reduce the number of intensity values in gray scale image from 256 to eight. The number of gray levels determines the size of the GLCM. To control the number of gray levels in the GLCM and the scaling of intensity values, using the Num Levels and the Gray Limits parameters of the graycomatrix function. See the graycomatrix reference page for more information.

The gray-level co-occurrence matrix can reveal certain properties about the spatial distribution of the gray levels in the texture image. For example, if most of the entries in the GLCM are concentrated along the diagonal, the texture is coarse with respect to the specified offset. You can also derive several statistical measures from the GLCM. See [Deriving Statistics from a GLCM](#) for more information.

To illustrate, the following figure shows how graycomatrix calculates the first three values in a GLCM. In the output GLCM, element (1,1) contains the value 1 because there is only one instance in the input image where two horizontally adjacent pixels have the values 1 and 1, respectively. glcm(1,2) contains the value 2 because there are two instances where two horizontally adjacent pixels have the values 1 and 2. Element (1,3) in the GLCM has the value 0 because there are no instances of two horizontally adjacent pixels with the values 1 and 3. graycomatrix continues processing the input image, scanning the image for other pixel pairs (i,j) and recording the sums in the corresponding elements of the GLCM.

	1	2	3	4	5	6	7	8
1	1	1	5	6	8			
2	2	3	5	7	1			
3	4	5	7	1	2			
4	8	5	1	2	5			

GLCM

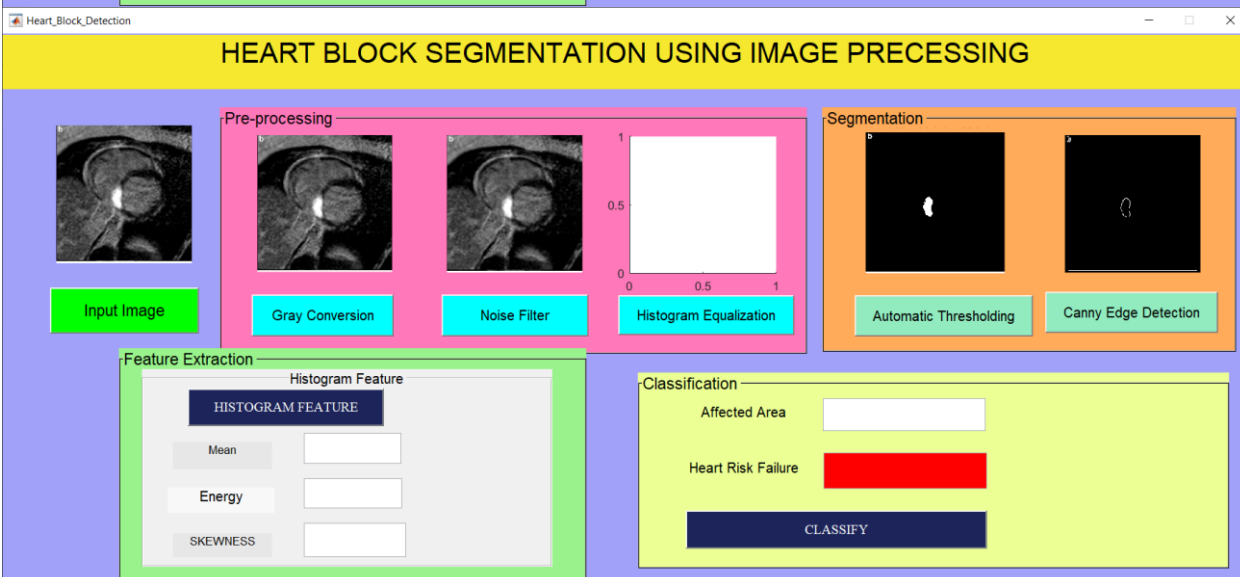
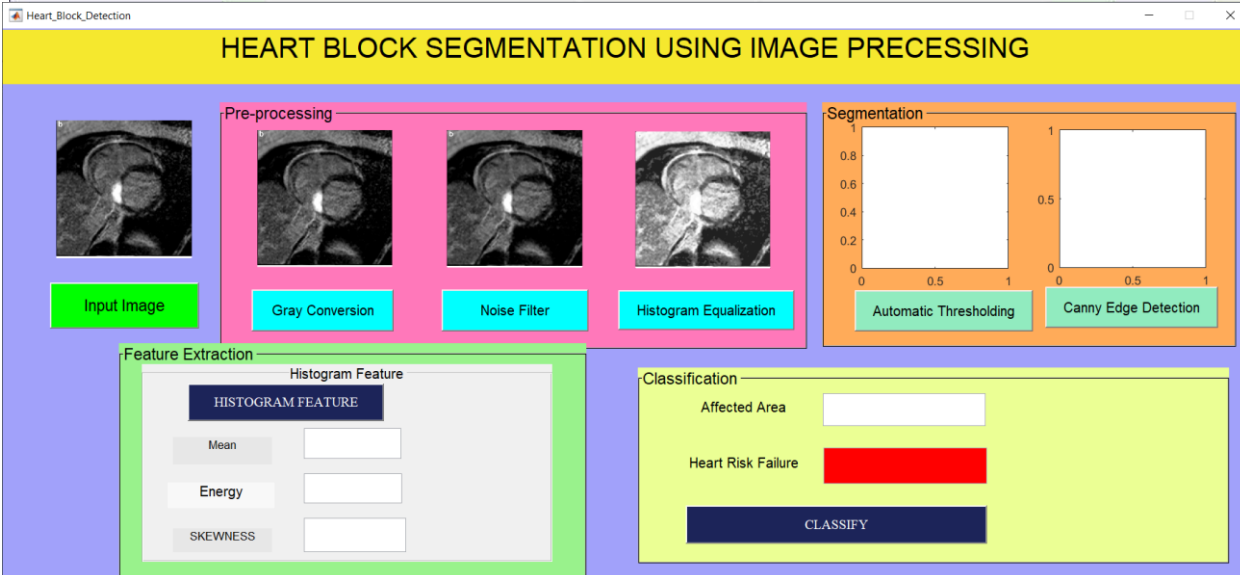
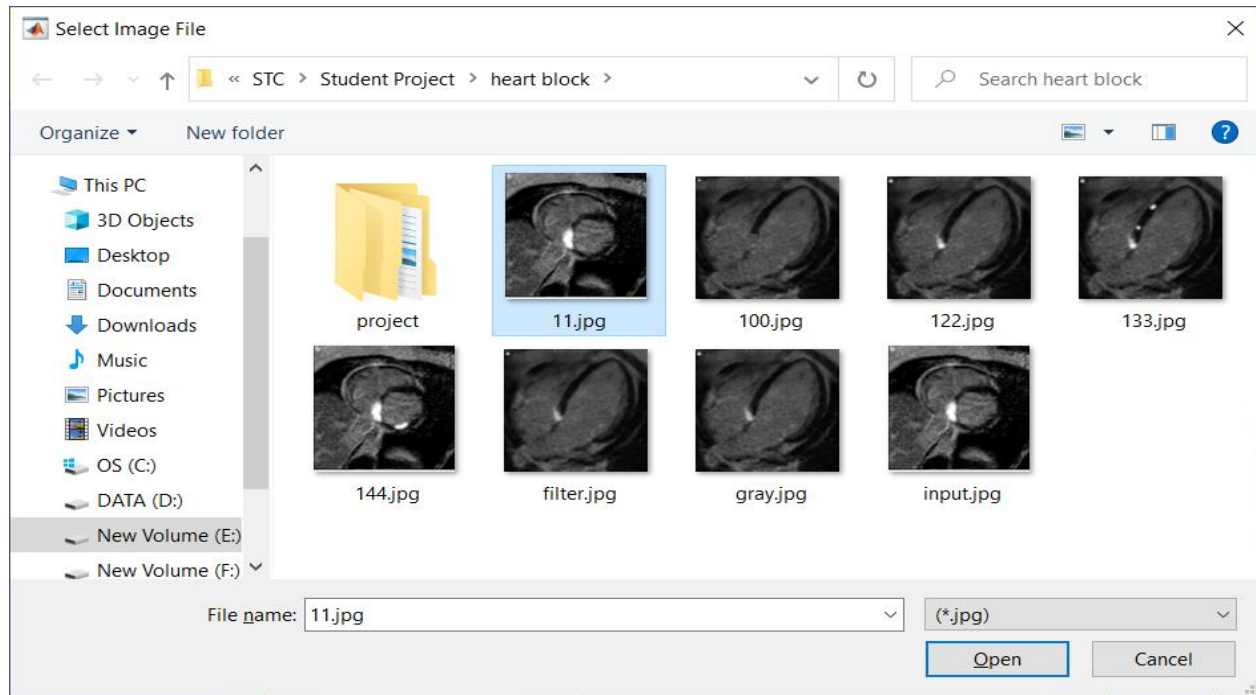
	1	2	3	4	5	6	7	8
1	1	2	0	0	1	0	0	0
2	0	0	1	0	1	0	0	0
3	0	0	0	0	1	0	0	0
4	0	0	0	0	1	0	0	0
5	1	0	0	0	0	1	2	0
6	0	0	0	0	0	0	0	1
7	2	0	0	0	0	0	0	0
8	0	0	0	0	1	0	0	0

CLASSIFICATION

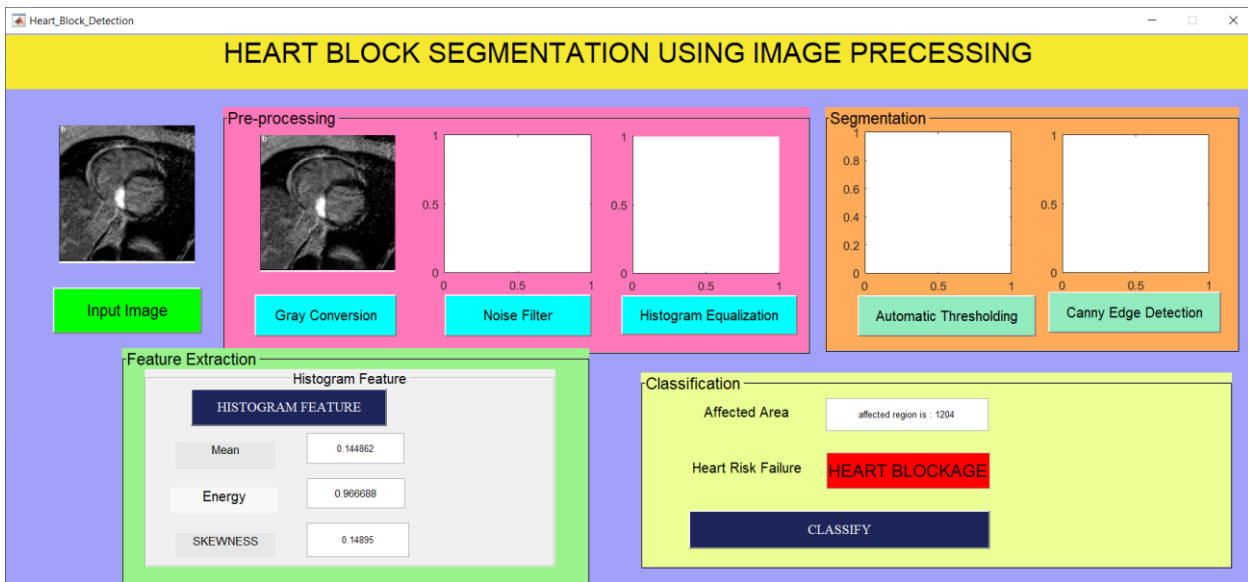
We can implement a KNN model by following the below steps:

1. Load the data
2. Initialize the value of k
3. For getting the predicted class, iterate from 1 to total number of training data points
 - Calculate the distance between test data and each row of training data. Here we will use Euclidean distance as our distance metric since it's the most popular method. The other metrics that can be used are Chebyshev, cosine, etc.
 - Sort the calculated distances in ascending order based on distance values
 - Get top k rows from the sorted array
 - Get the most frequent class of these rows
 - Return the predicted class

4. RESULTS



HEART BLOCK SEGMENTATION USING IMAGE PRECESSING



Pre-processing

Input Image | Gray Conversion | Noise Filter | Histogram Equalization

Segmentation

Automatic Thresholding | Canny Edge Detection

Feature Extraction

Histogram Feature

HISTOGRAM FEATURE	
Mean	0.144862
Energy	0.966688
SKEWNESS	0.14895

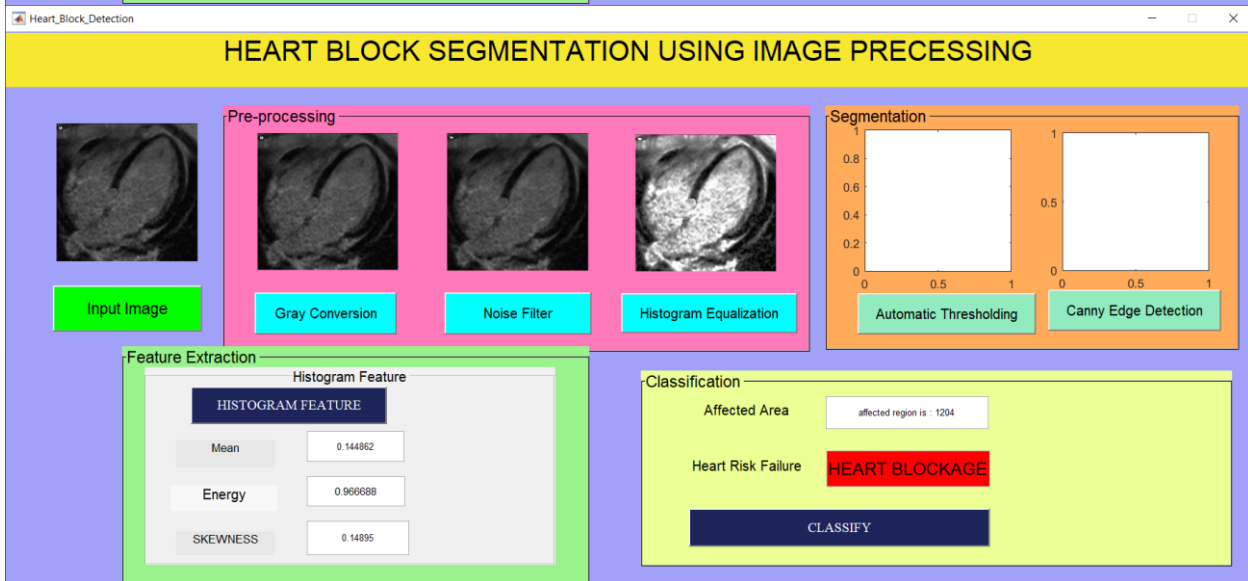
Classification

Affected Area: affected region is : 1204

Heart Risk Failure: **HEART BLOCKAGE**

CLASSIFY

HEART BLOCK SEGMENTATION USING IMAGE PRECESSING



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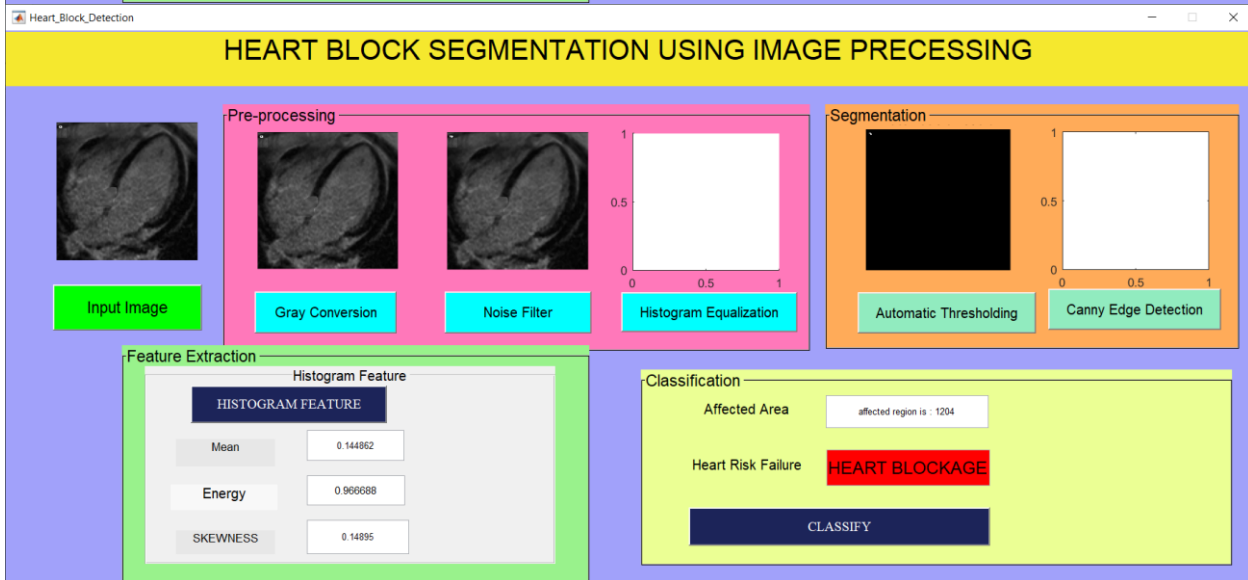
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CLASSIFY



5. CONCLUSION

All the discussion and evaluation that has been used in this paper was carried out through huge dataset in order to ensure the reliability. Finally, it can be said that, the whole purpose of this research is to create an autonomous system of an existing system. The already existing system relies on the evaluation of a doctor which can vary depending on a number of factors. However, since our newly created system doesn't rely on human judgment at all, its generated report won't differ for the same input. Again, in order to evaluate the perfection of the proposed system, the results were shown to a number of doctors. The doctor's report and the report developed by our system has approximately an 80% match.

6. REFERENCE

- [1] A.Farhad. 2014 "K-means clustering based angiographic image analysis to measure coronary stenosis", Eastern Mediterranean University.
- [2] S. Agrawal, "Automated Segmentation of Cardiac Stenosis and Mathematical Modeling of Myocardial Blood Flow for Early Detection of Heart Attack Using Advanced Imaging Techniques", IOSR Journal of Computer Engineering, vol. 16, no. 6, pp. 41-47, 2014.
- [3] R.Shahzad, S.Michiel, F.B. Goncalves, C.T.Metz, T.Hui, T.V.Walsum, A.Moelker, L.J.Vliet, & W.J.Niessen. "Automatic detection of calcified lesions in the descending aorta using contrast enhanced CT scans". Biomedical Imaging (ISBI), 2012 9th IEEE International Symposium on, pp. 250-253, 2012.
- [4] A.Wahle, E.Wellnhofer, I.Mugaragu, H.U.Saner, H.Oswald & E.Fleck, "Assessment of diffuse coronary artery disease by quantitative analysis of coronary morphology based upon 3-D reconstruction from biplane angiograms". IEEE Transactions on Medical Imaging, vol. 14, no. 2, pp. 230-241, Jun 1995.
- [5] P. Nikos, "Geodesic active regions: A new framework to deal with frame partition problems in computer vision." Journal of Visual Communication and Image Representation, vol. 13, pp. 249- 268, 2002.
- [6] M.Mazinani, S.D.Qanadli, R.Hosseini, E.T.Dehmeshki , "A 3D Approach for Extraction of the Coronary artery and Quantification of the Stenosis", World Academy of Science, Engineering and Technology International Journal of Biomedical and Biological Engineering, vol. 5, no. 11, 2011.