ED6001 Medical Image Analysis

Assignment 2

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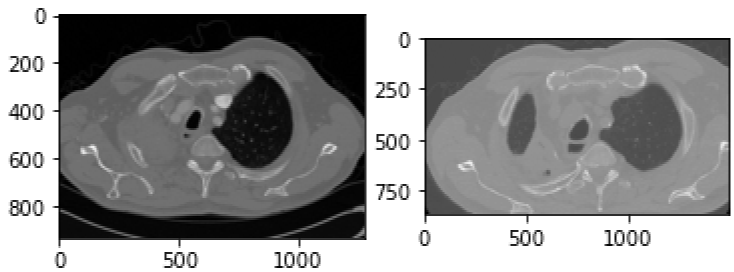
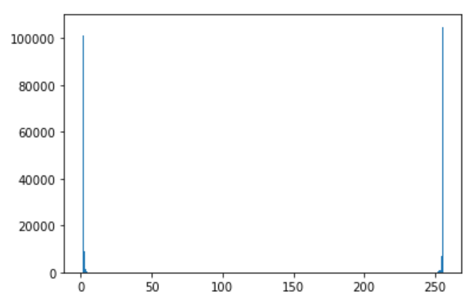
ED18B009

Part 1

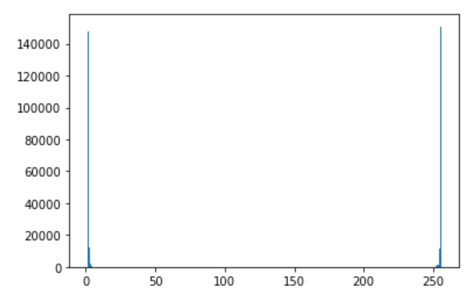


Original CT Images

CT images are prone to Gaussian noise and Quantum noise according to the class notes and this paper. However, we don't know exactly how these images were acquired or how they were processed later after acquisition. Thus to check if the image had gaussian noise, we filter it using the mean filter and then look at the histogram of the residual.

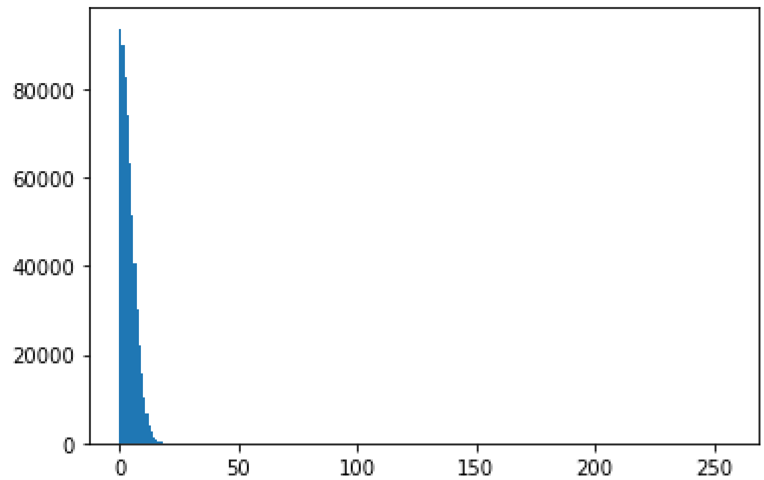


Histogram of the residual (image 1)

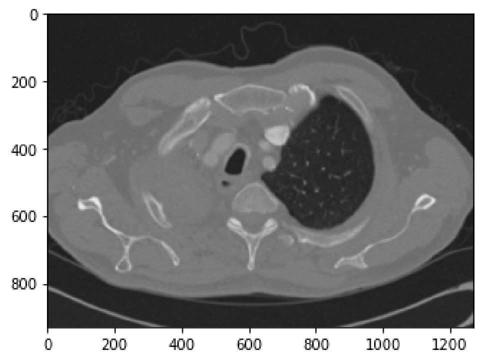


Histogram of the residual (image 2)

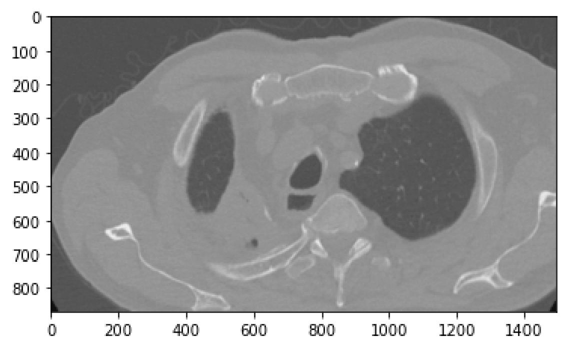
The distribution does not resemble a normal distribution, thus the assumption of gaussian noise being present is not appropriate here. Therefore, we add Gaussian noise manually with mean zero and variance 5.



Gaussian noise to be added



Noisy Image 1



Noisy Image 2

Observations

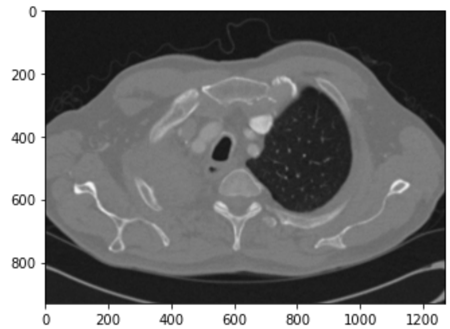
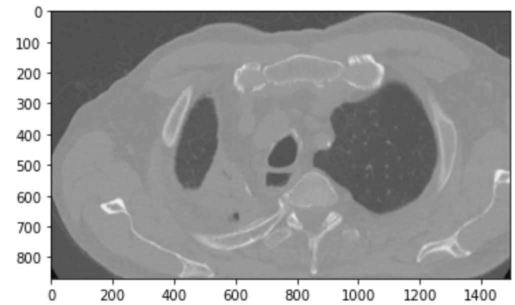
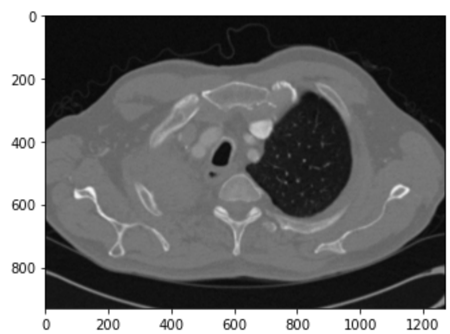
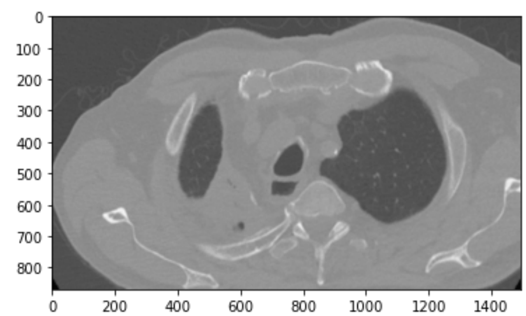
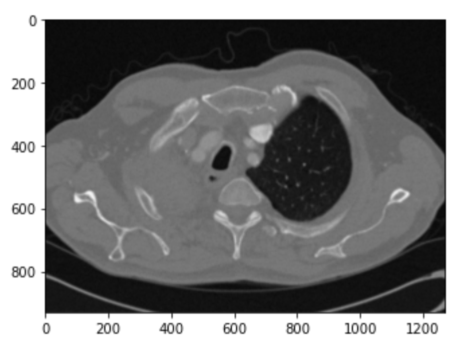
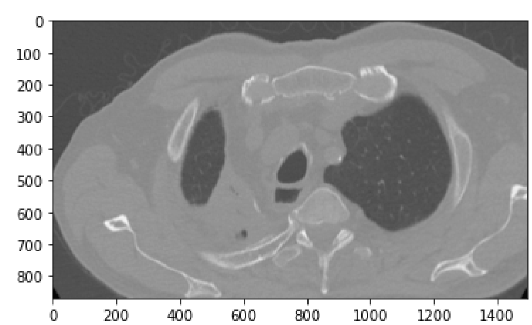
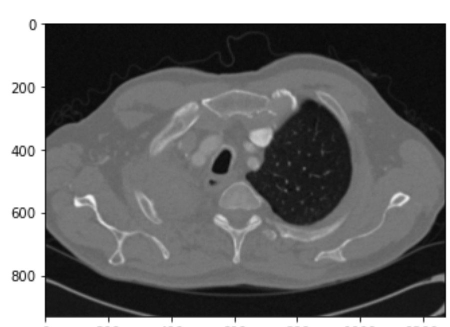
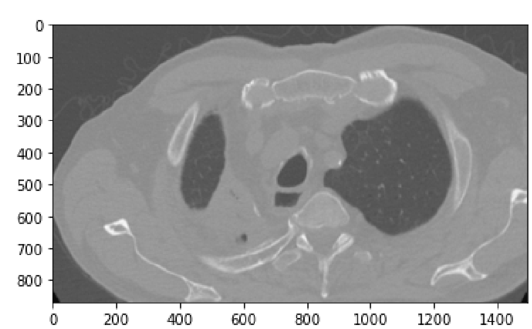
Filter used	Image 1	Image 2
Weiner		
Gaussian		
Mean		
Median		

Image 1

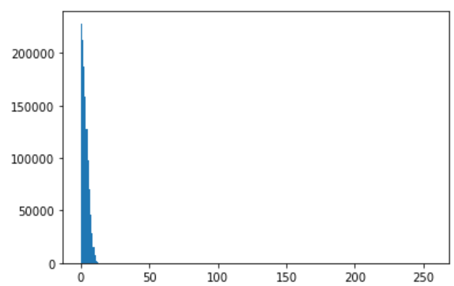
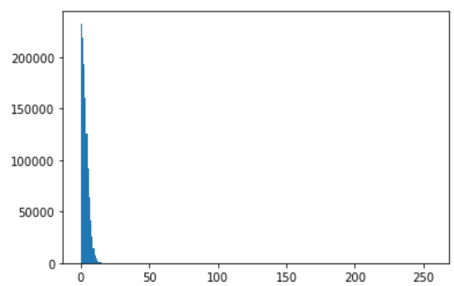
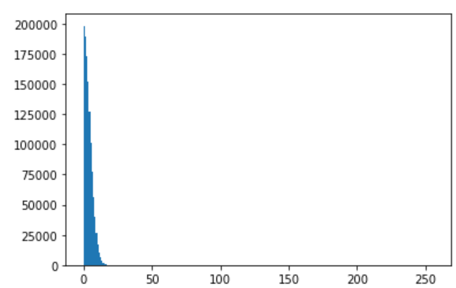
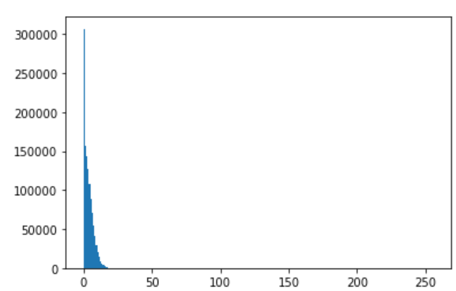
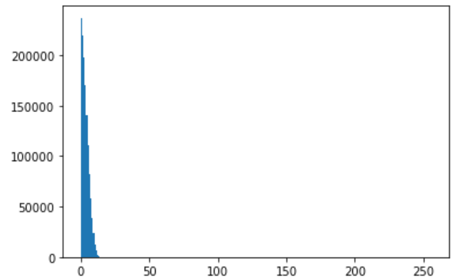
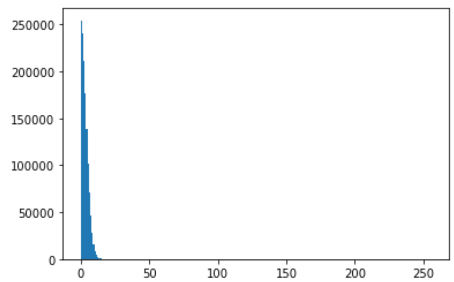
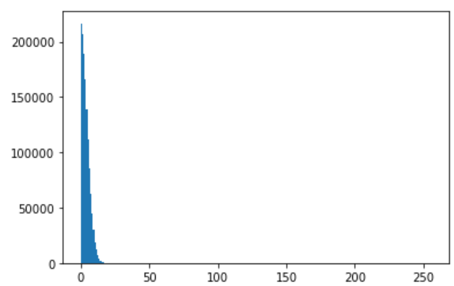
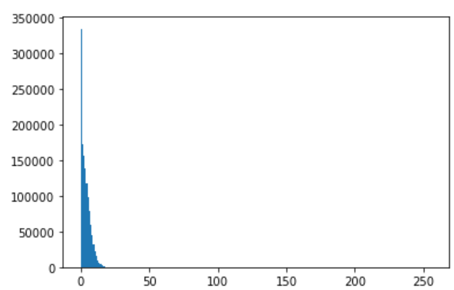
Filter used	Histogram of Residual	PSNR
Weiner		14.14476
Gaussian		14.14527
Mean		14.14638
Median		14.14415

Image 2

Filter Used	Histogram of the residual	PSNR
Weiner		14.14535
Gaussian		14.14452
Mean		14.14557
Median		14.14343

Inferences

- Histogram of the residual image resembles a normal distribution with mean zero for mean, gaussian and wiener filters. Median filter on the other hand does not do a very good job in removing the gaussian noise as we can see from the histogram of the residual. This is also reflected in the PSNR value for the median filter.

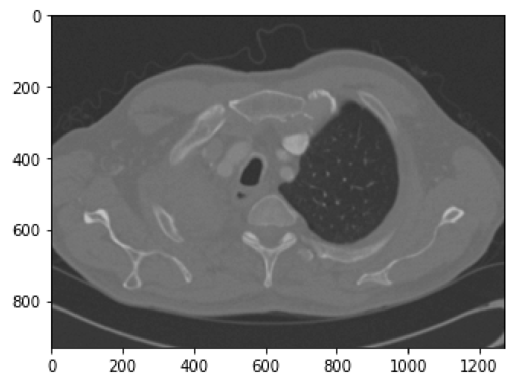
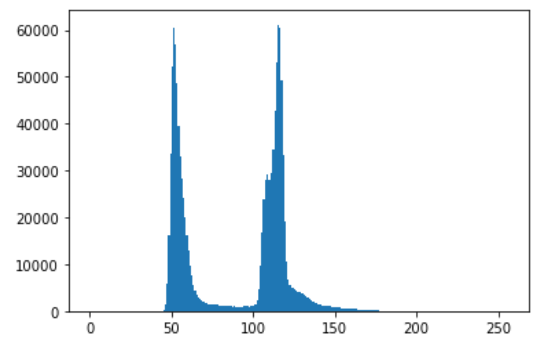
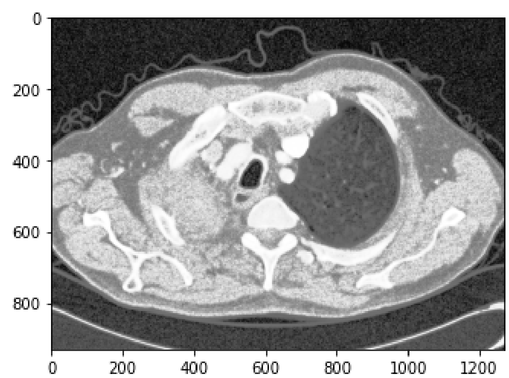
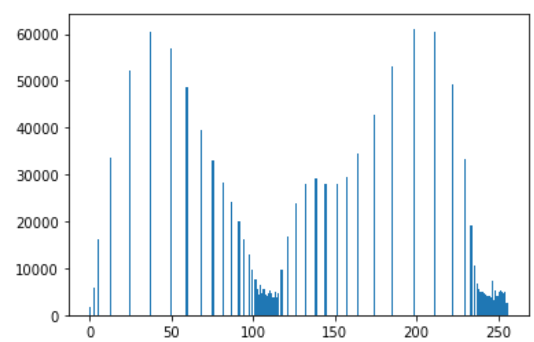
- According to the PSNR values, the order of efficiency of noise removal by different filters is Mean > Gaussian > Wiener >> Median.
- This is reflected in the observations for both images.
- Thus, we can conclude that the mean filter works the best for removing gaussian noise from images. We use these mean filtered images for the next part of the assignment.

Part 2

Contrast Enhancement

Observations

Image 1

	Image	Histogram
Original Image		
Histogram Equalized Image		

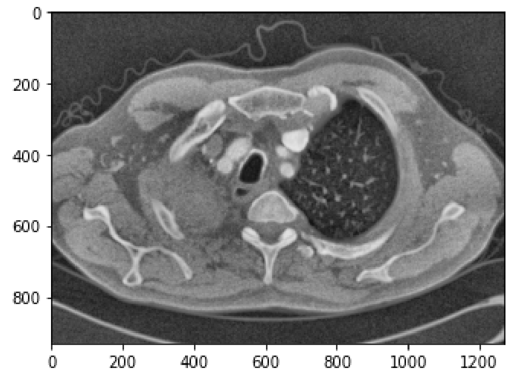
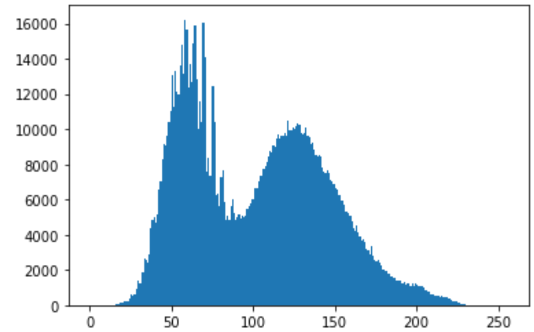
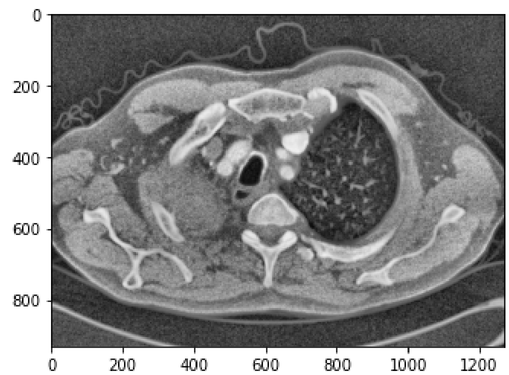
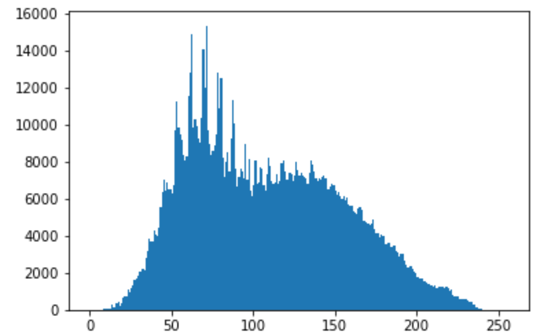
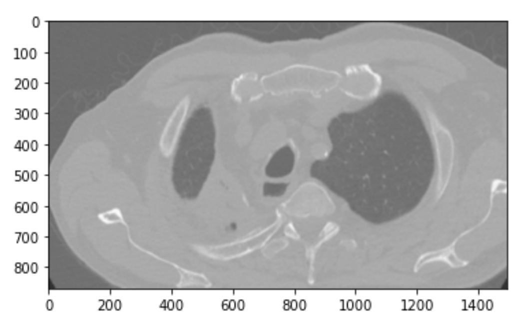
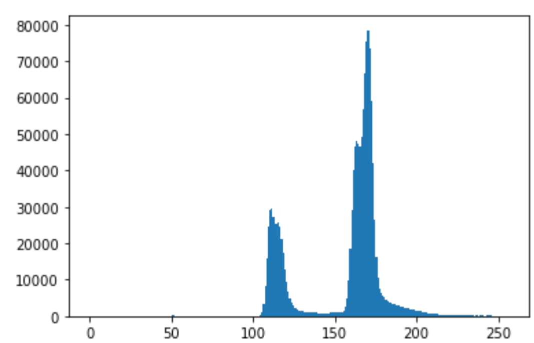
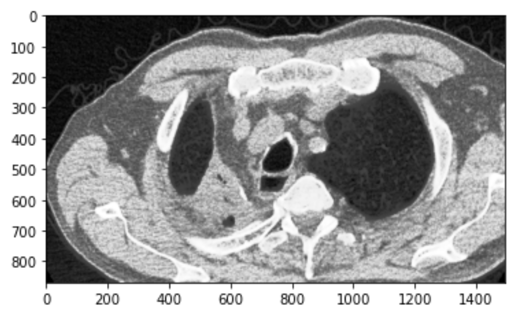
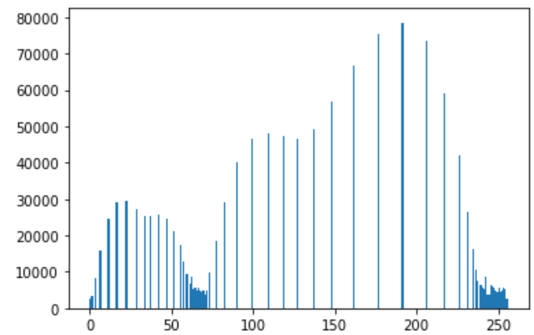
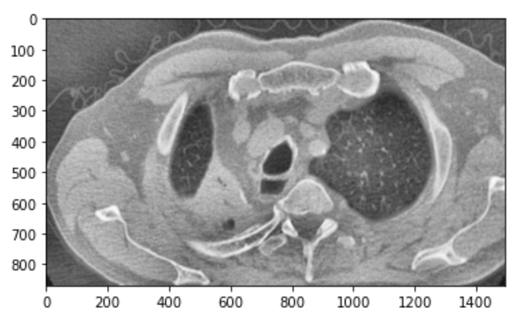
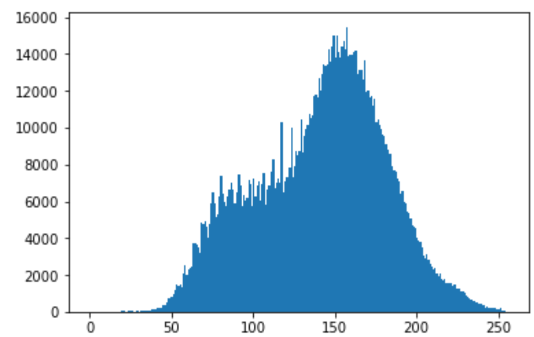
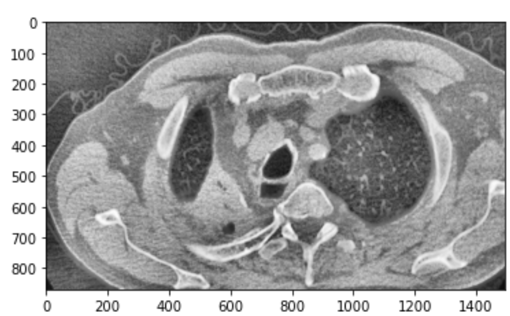
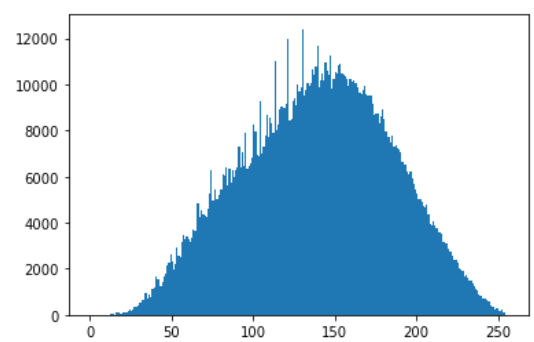
Clahe with cliplimit = 5		
Clahe with cliplimit = 8		

Image 2

	Image	Histogram
Original Image		

Histogram Equalized Image		
Clahe with cliplimit = 8		
Clahe with cliplimit = 8		

Inferences

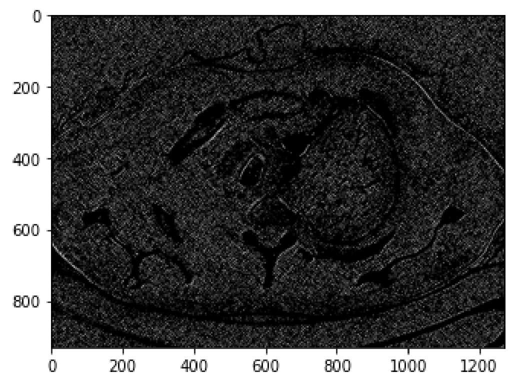
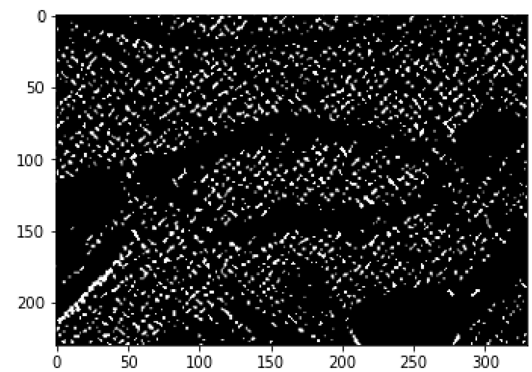
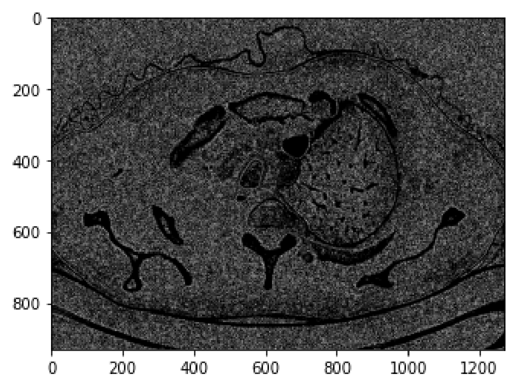
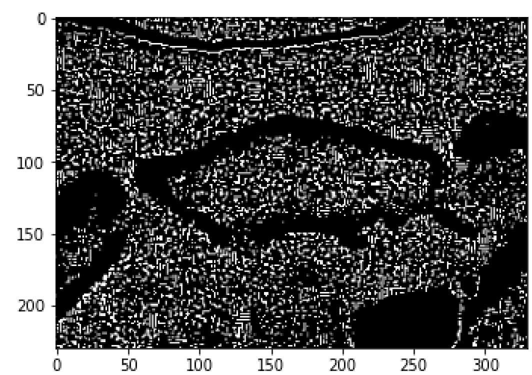
- We use histogram equalization and CLAHE method with different cliplimits for contrast enhancement.
- Histogram equalization technique takes the global context into consideration, this includes the dark background which we don't care about much. Thus the enhanced image treats the whole body as foreground, whereas we need segmentation of a specific part (sternum).
- CLAHE on the other hand uses local windows, thus when iterating over the part of the image containing the sternum, it treats it as the foreground and we get better contrast there.

- Experimenting with different values, setting the cliplimit at 8 works the best.

Edge Detection

Observations

Image 1

	Original Image	Cropped Image (Sternum)
Sobel		
Laplacian		

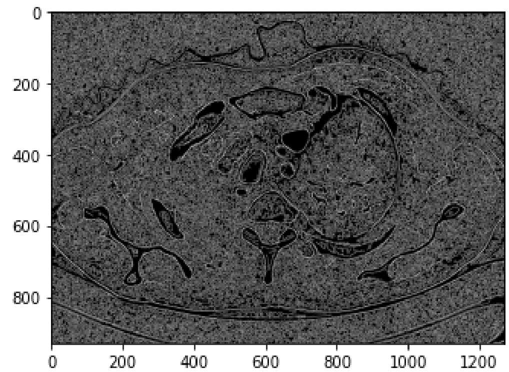
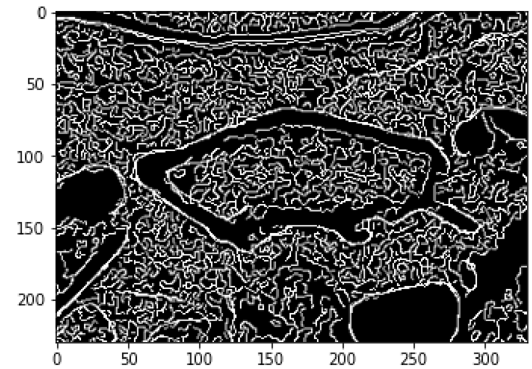
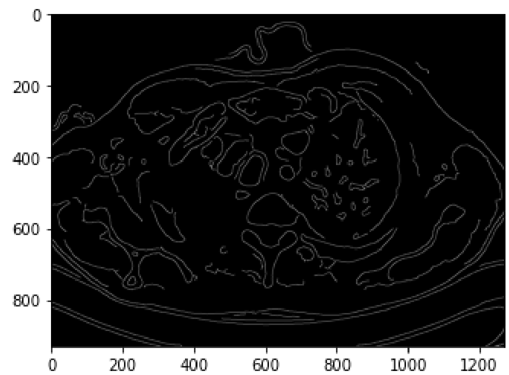
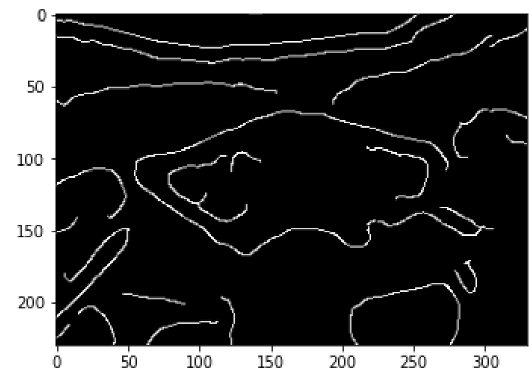
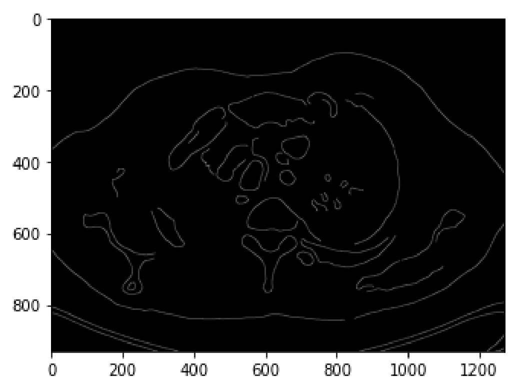
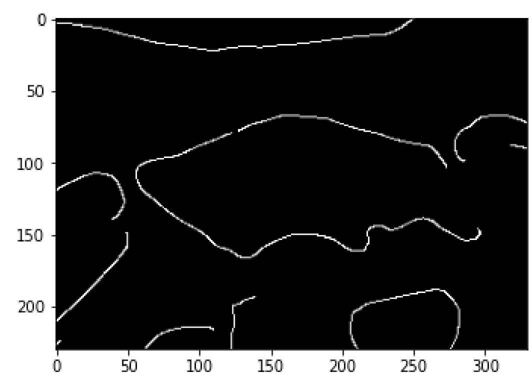
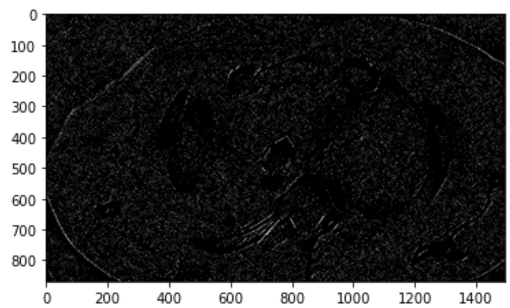
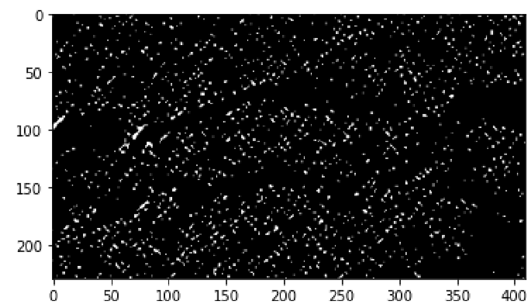
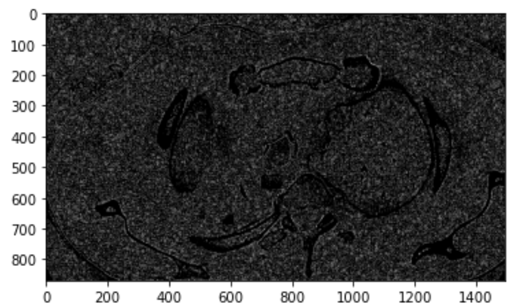
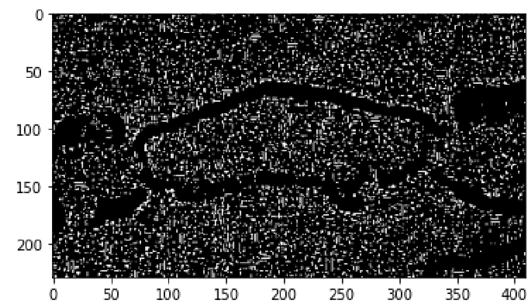
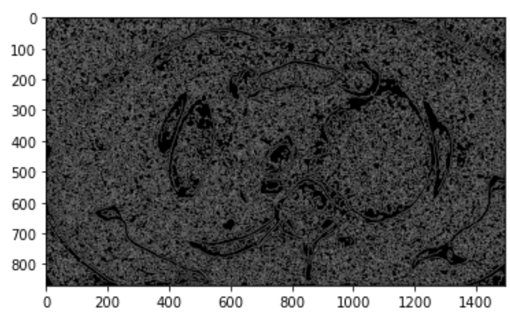
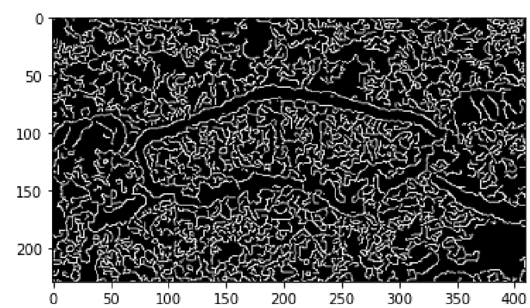
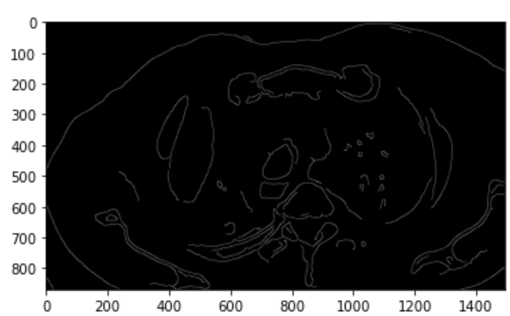
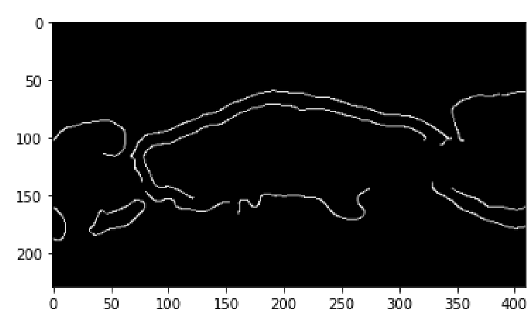
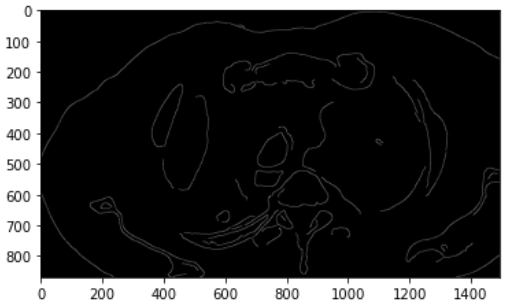
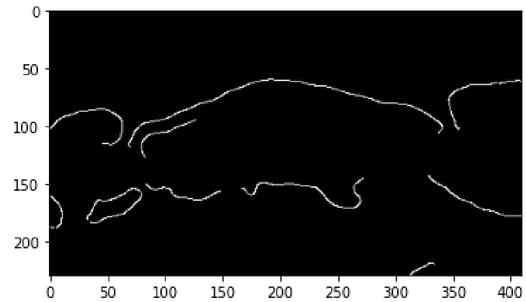
Canny (Sigma = 1)		
Canny (Sigma = 3)		
Canny (Sigma = 4)		

Image 2

	Full Image	Cropped Image (Sternum)
sobel		
laplacian		
Canny (Sigma = 1)		
Canny (Sigma = 3.5)		

Canny (Sigma = 4)		

Inferences

- We use various edge detection including Laplacian filter, Sobel filter and Canny edge detection to find the contour of the sternum.
- Unlike the Sobel edge detector, the Laplacian edge detector uses only one kernel. It calculates second order derivatives in a single pass. Because it approximates the second order derivative, it is very sensitive to noise. We can see this in the image.
- Laplacian and Sobel filtering techniques are far less computationally expensive than the Canny edge detection technique. This was expected since Canny edge detection first blurs the image, then filters the image using an edge detection filter (Sobel) and then extracts and connects the edges.
- However since we are looking for the contour of the sternum to perform Hough transform on, it’s more efficient to spend more computational power here than on the Hough transform.
- The Canny method has an adjustable parameter - the width of the Gaussian (the noisier the image, the greater the width). We can look at the images and see that as the sigma increases, the noise decreases. However, we also lose some part of the signal at higher sigma values. Thus we choose an appropriate sigma value after considering the tradeoff.

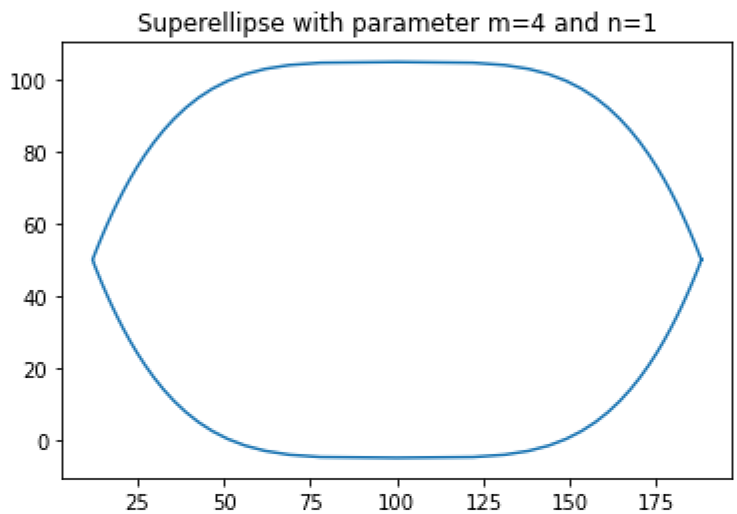
Part 3

Approach:

Parametric equation for a generalized superellipse is given by -

$$x\left(t\right) = \left|\cos t\right|^{\frac{2}{m}} \cdot a \operatorname{sgn}(\cos t)$$
$$y\left(t\right) = \left|\sin t\right|^{\frac{2}{n}} \cdot b \operatorname{sgn}(\sin t).$$

After experimenting with multiple values for m and n, the best value to imitate a sternum-like curve was (m,n) = (4,1)



Equation for a Lamet curve with parameters (m,n) = (4,1) is given by -

$$C_{a,b} \; : \; bx^4 \; + \; a^4y \; = \; a^4b$$

We want to reduce the parameter space to 2. Therefore ideally we would like to iterate for different values of a and b only. We crop the image such that the center of the image coincides with the center of the sternum so as to not worry about finding the coordinates of the center of the Lamet curve.

Thus by making two assumptions -

a. The center of the image coincides with the center of the sternum

b. The sternum's orientation is horizontal

We reduce the parameter space to just a and b.

Therefore from the equation of the Lamet curve, we can find an equation for the same in the parameter space *(A,B)*.

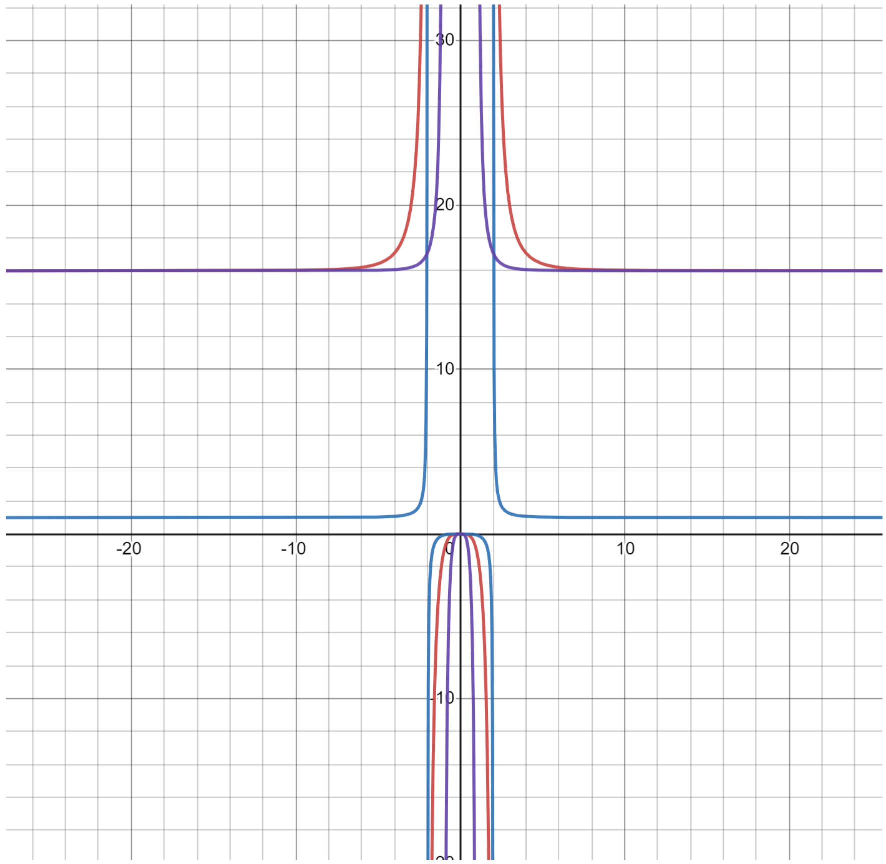
$$A^4B - Bx_p^4 - A^4y_p = 0$$

We can further parameterize this equation for the ease of calculation.

$$A = t$$

$$B = \frac{t^4y_p}{t^4 - x_p^4}$$

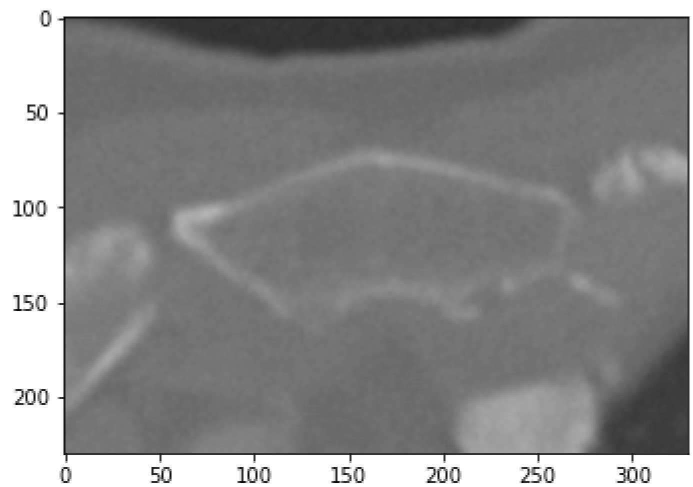
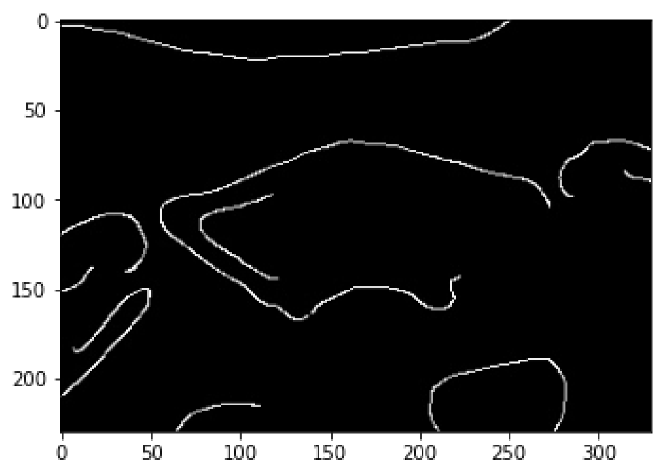
By plotting this equation for multiple values of (x_p, y_p), we can see that the curve has asymptotes at B = $y_p{}^4$ and A = x_p.



Since we are iterating over different values of t, we can define the range for A. Therefore we don’t have to care about horizontal asymptotes. However, to avoid vertical asymptotes we choose the range of t such that it starts with $x_p + 1$. This way we also avoid the coincidence of the curves at the origin.

Observations:

Image 1

<table>
<tr><td>Cropped Image</td><td>
</td></tr>
<tr><td>After Canny Edge Detection</td><td>
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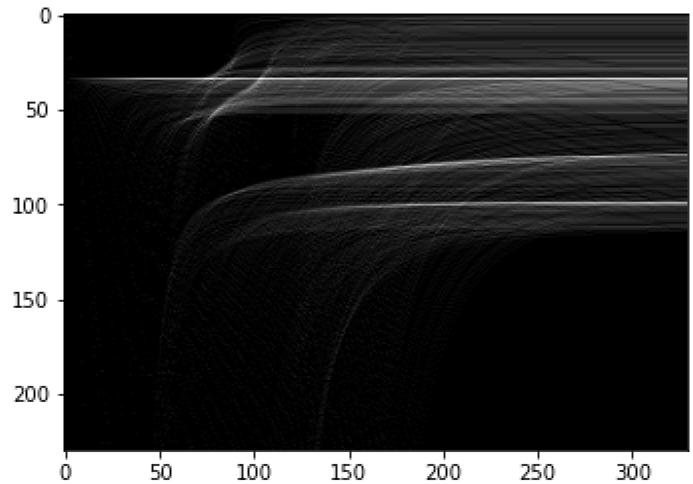
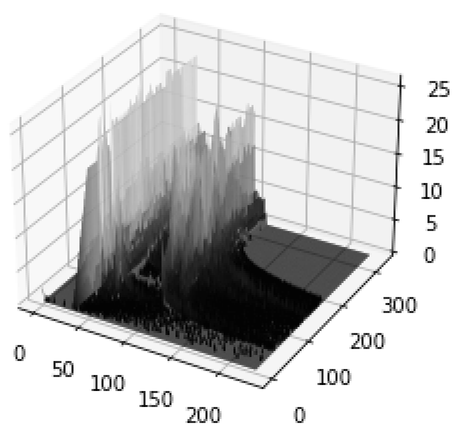
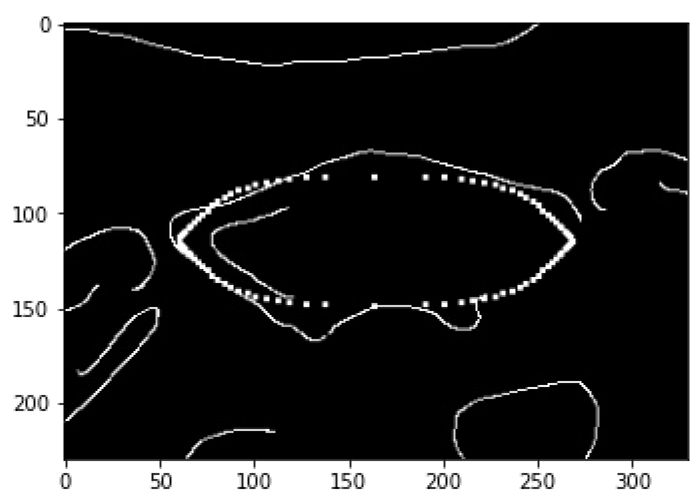
Hough Transforms of the Points	
Accumulator Function	
Recognized curve associated to the maximum of the accumulator	

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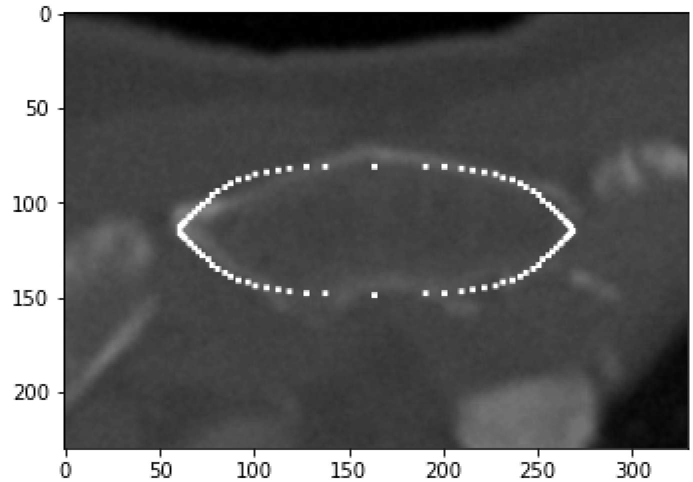
<tr><td>Drawing the curve on the original image</td><td>
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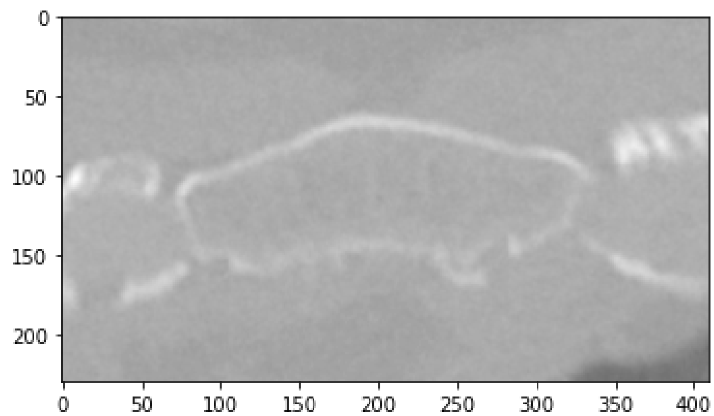
Image 2

<table>
<tr><td>Cropped Image</td><td>
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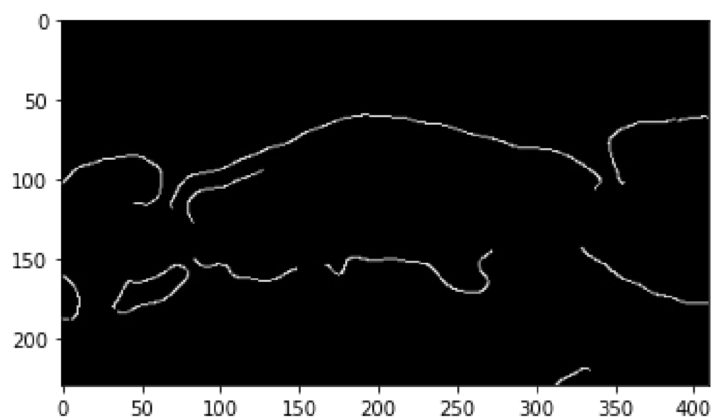
<tr><td>After Canny Edge Detection</td><td>
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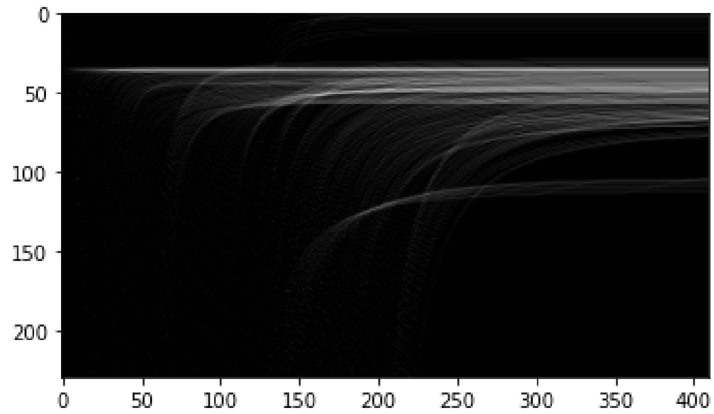
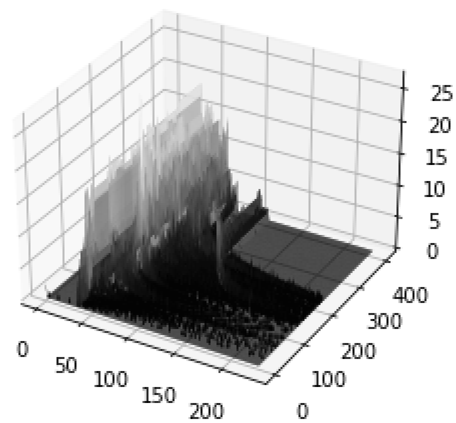
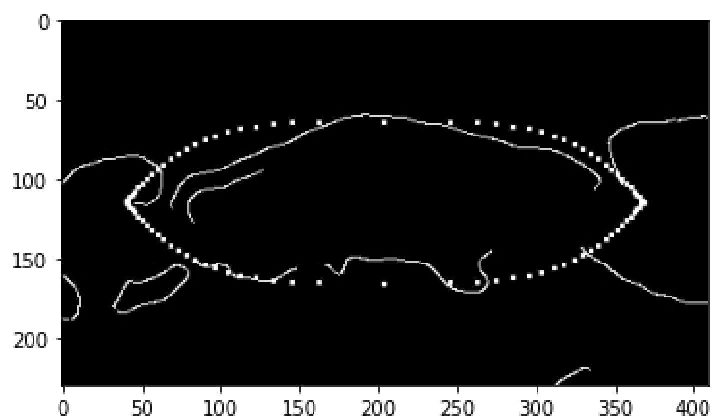
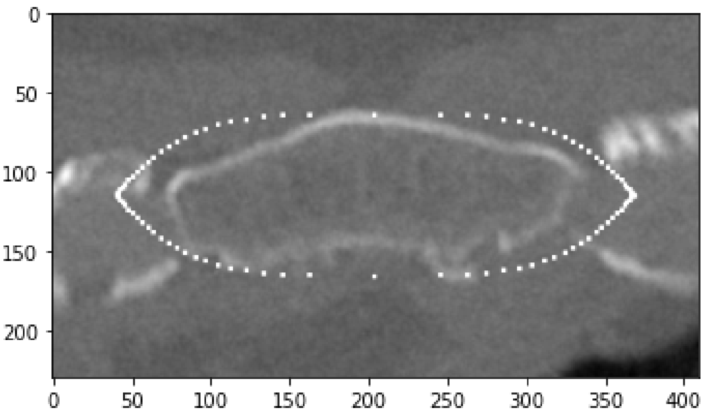
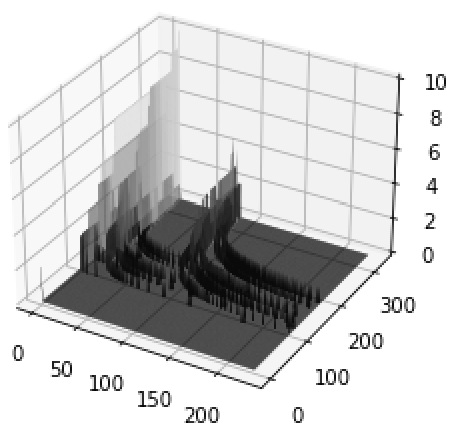
Hough Transforms of the Points	
Accumulator Function	
Recognized curve associated to the maximum of the accumulator	

Drawing the curve on the original image	

Inferences

- It is important to choose the appropriate values for m and n. We should choose the curve that resembles the shape of the object the most.
- If we choose the value of m and n both to be 4, when deriving the parametric equation for B, we get y_p^4 in the numerator. Our limited parameter space may not be able to accommodate such huge values. This leads to flat asymptotic values in our accumulator function shown in the following figure.



- m = 4 and n = 1 work the best for approximating the sternum.