Ryerson University
Department of Electrical & Computer Engineering
Faculty of Engineering & Architectural Science

Course Title:	Biomedical Image Analysis
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Instructor:	April Khademi

Assignment/Lab Number:	3
Assignment/Lab Title:	Automatic Edge and Vessel Detection in Retinal Images

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Reset Form

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BME 872 - Lab 3

2.1 Filtering Functions

1. **Image Smoothing**

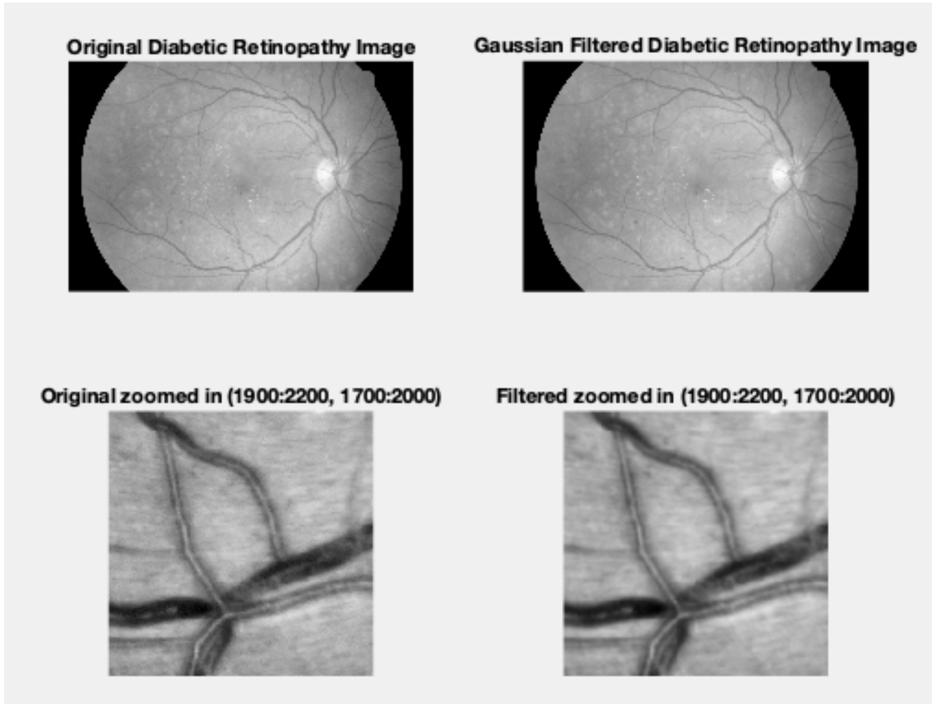

Figure 1: Original and gaussian filtered diabetic retinopathy image

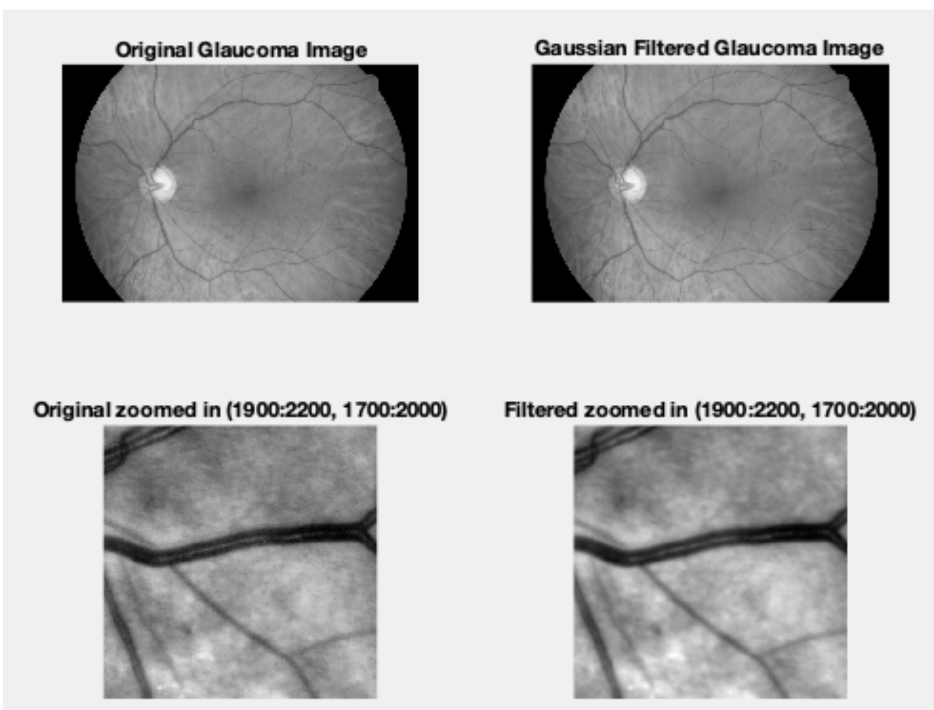

Figure 2: Original and gaussian filtered glaucoma image

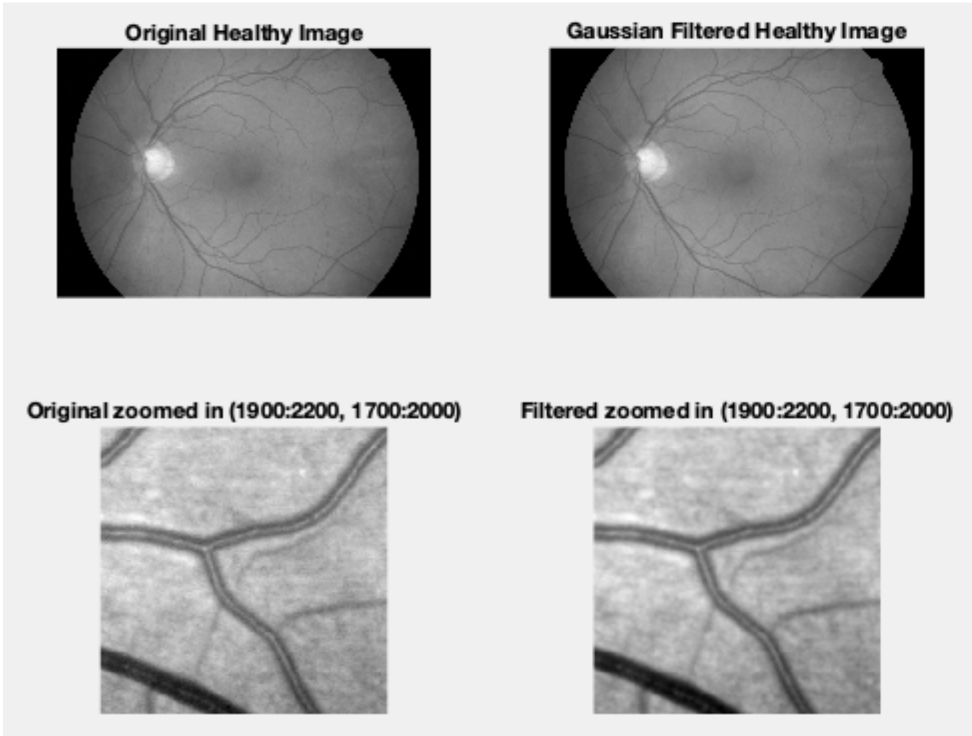

Figure 3: Original and gaussian filtered healthy image

2. Edge Detection

```
>> help derivative_kernel
  A function to give you the derivatve filter kernel that you desire

    Input: String that will indicate which derivative filter kernel
           Options - Central, Forward, Prewitt, Sobel

    Output: Derivative filter kernel's coefficients
```

Figure 4: Demonstration of the help function working for derivative_kernel function

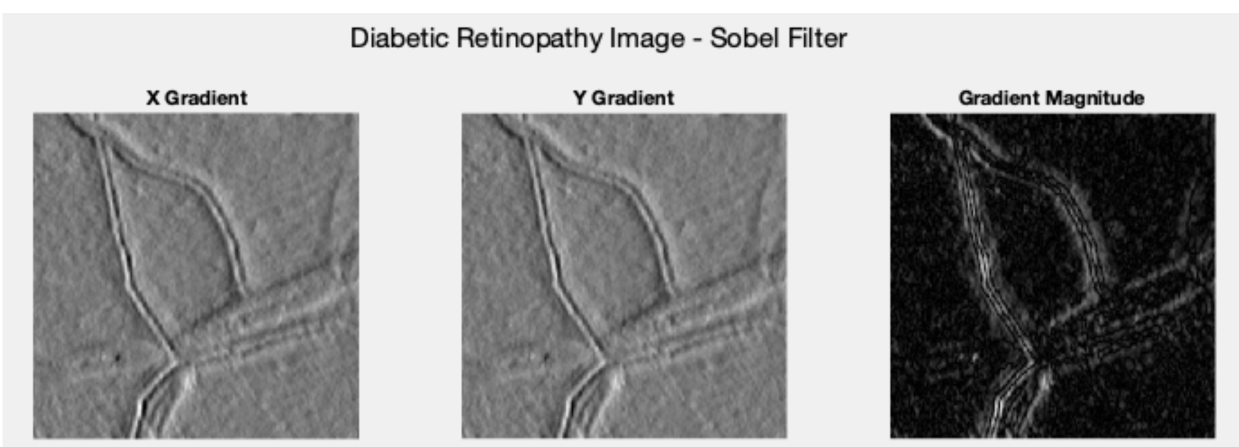

Figure 5: X & Y gradient and gradient magnitude images for a diabetic retinopathy subject using the sobel filter

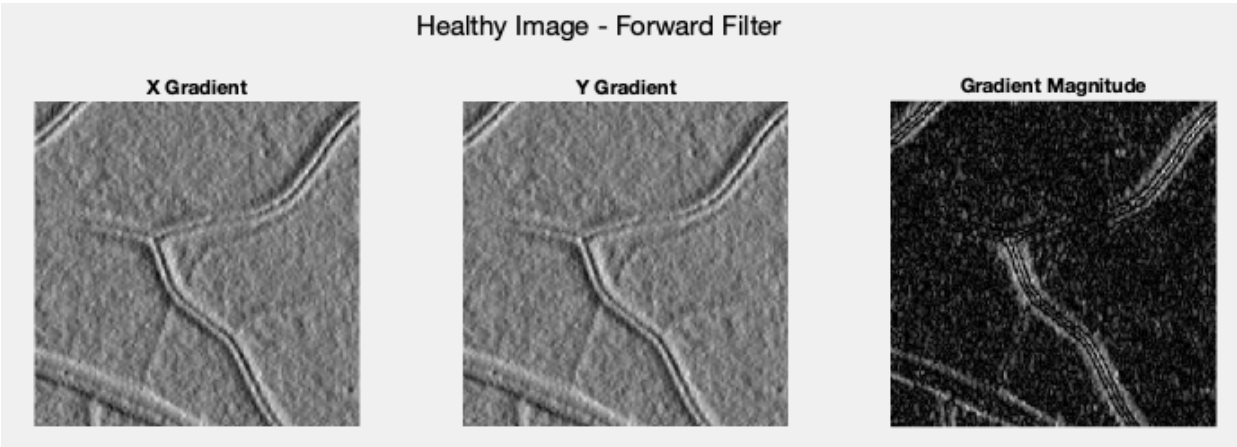

Figure 6: X & Y gradient and gradient magnitude images for a healthy subject using the forward filter

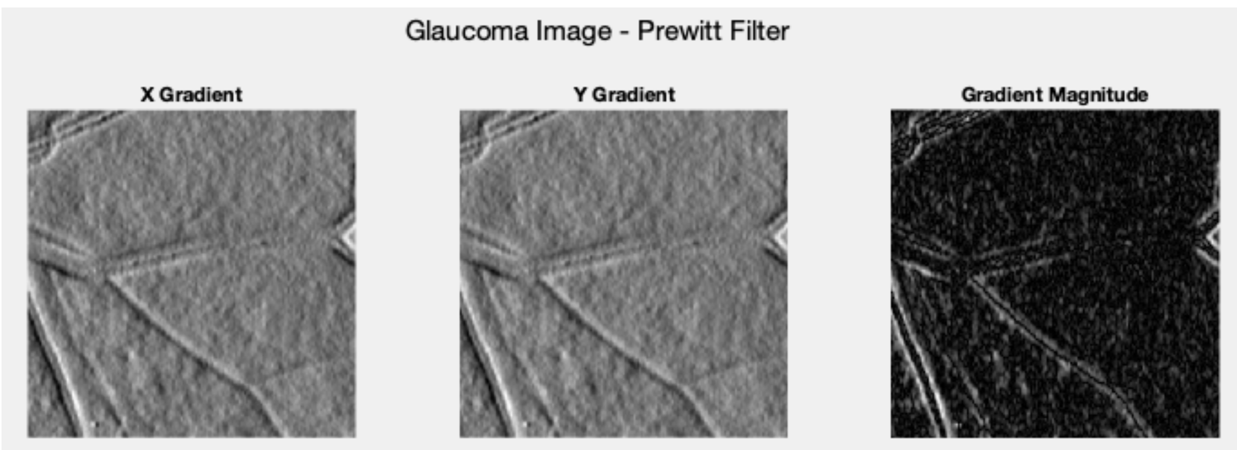

Figure 7: X & Y gradient and gradient magnitude images for a glaucoma subject using the prewitt filter

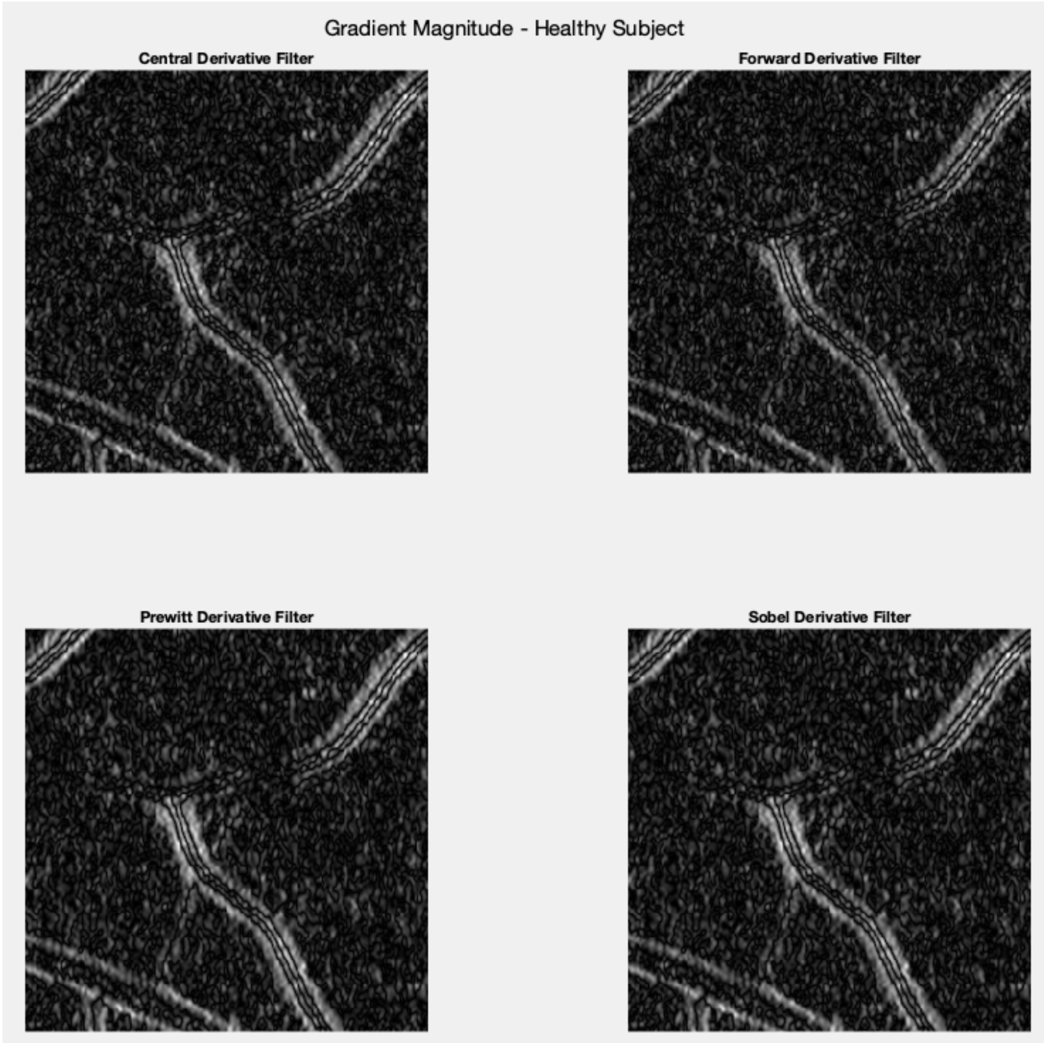

Figure 8: Comparison of the four derivative filters for a healthy subject

The observable difference between each kernel was very minimal. The Sobel kernel tended to perform the best in terms of defining edges, however it also highlighted some of the unwanted noise. The Prewitt also performed fairly well, but seemed to have more noise. The central and forward difference seemed to have marginally less edge contrast than the other two options. Overall the Sobel filter seems to perform the best for this application.

2.2 Non-Maxima Suppression

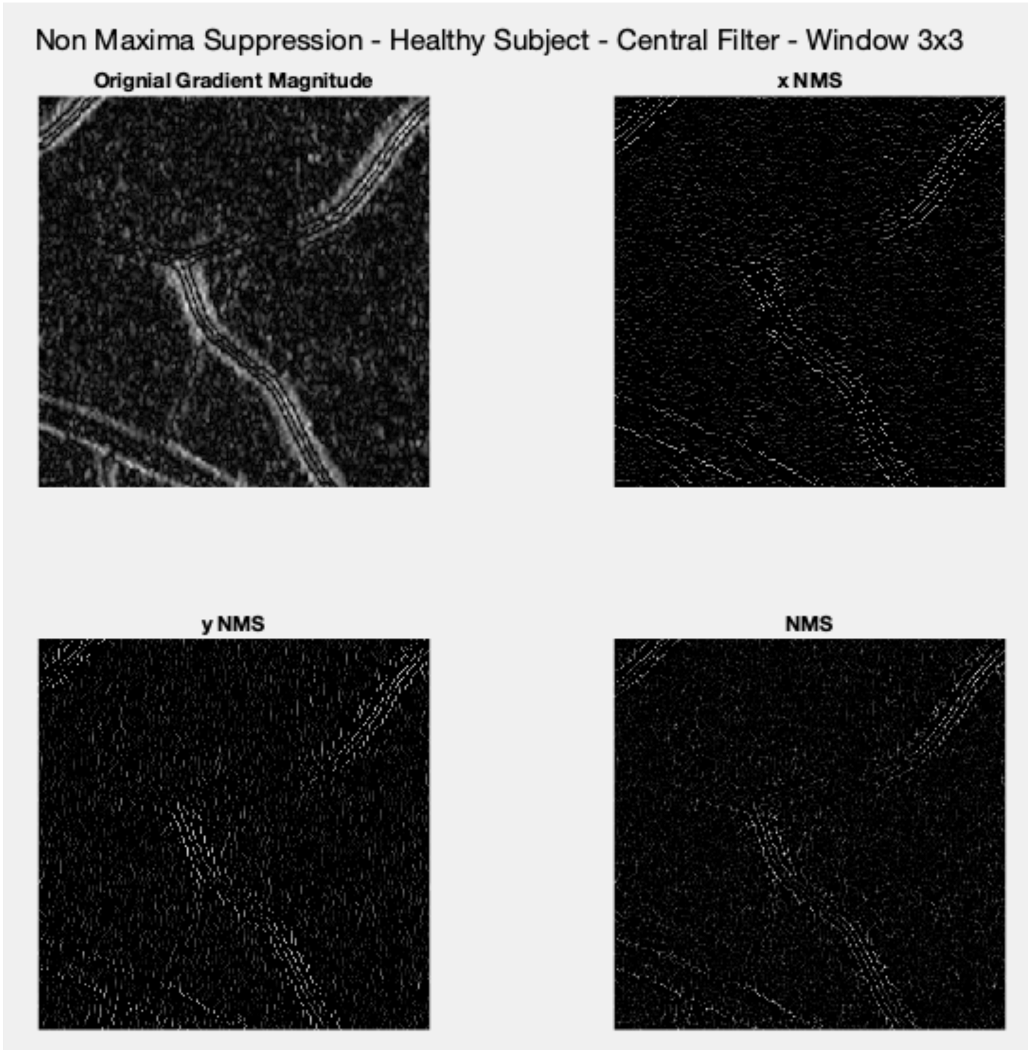

Figure 9: Non maxima suppression results for a 3x3 window

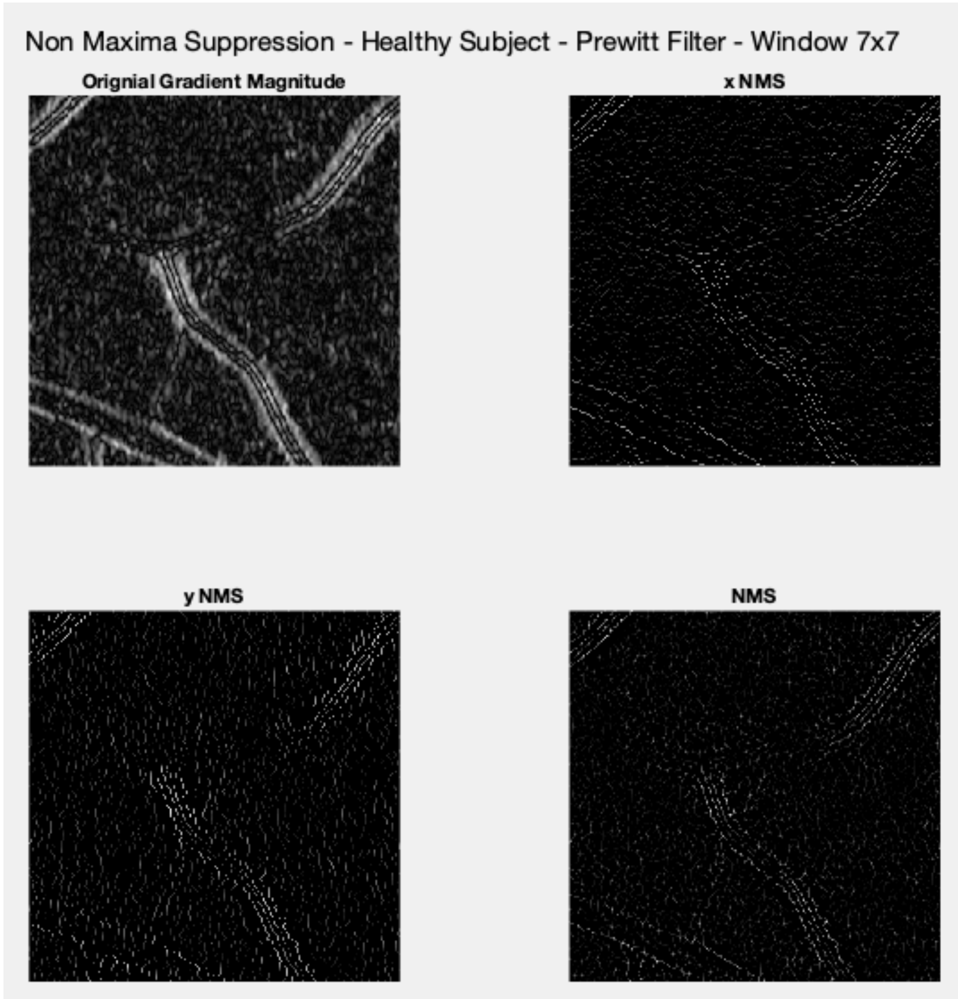

Figure 10: Non maxima suppression results for a 7x7 window

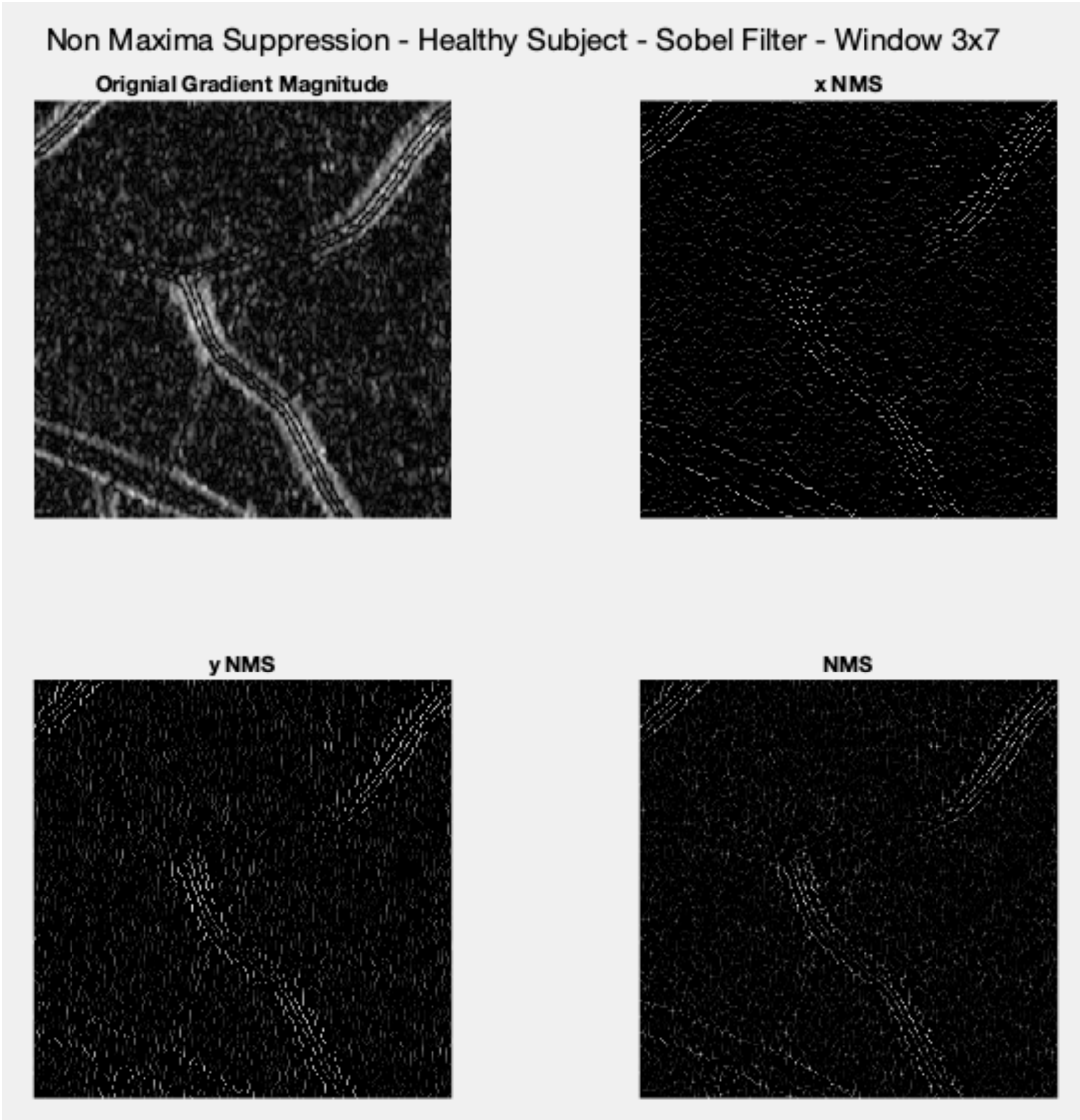

Figure 11: Non maxima suppression results for a 3x7 window

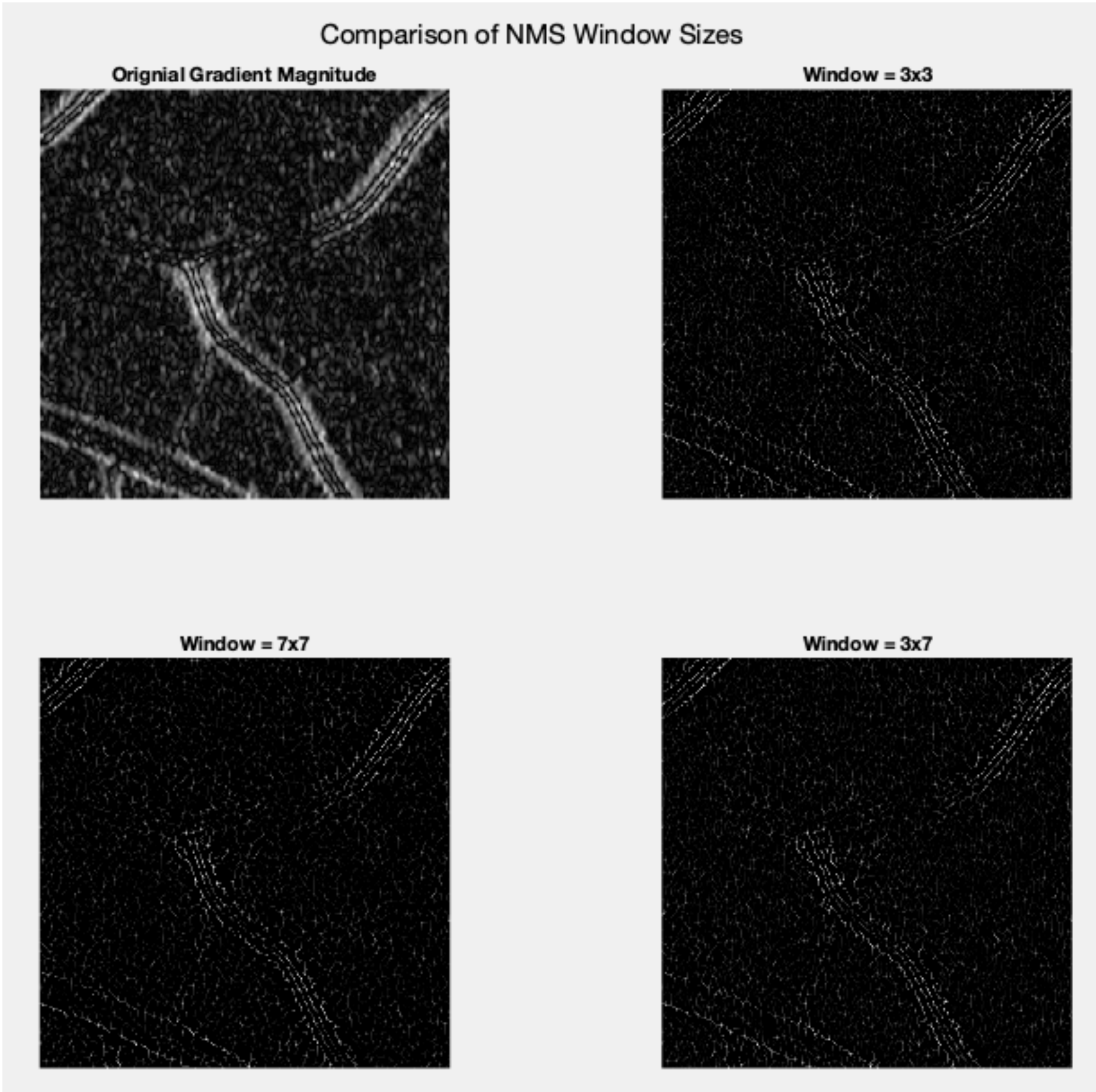

Figure 12: Comparison of non maxima suppression results for different window sizes

The larger window size tends to make the image more blurry. Size of the window ideally should depend on the relative size of the features of being observed. The 3x7 window was interesting because it caused the emphasis on vertical lines, as the horizontal edges were fairly well suppressed. This might be beneficial when you are specifically interested in an image with distinct vertical patterns, or patterns in a specific direction. It was more efficient to apply two one-dimensional windows for computational efficiency.

2.3 Threshold

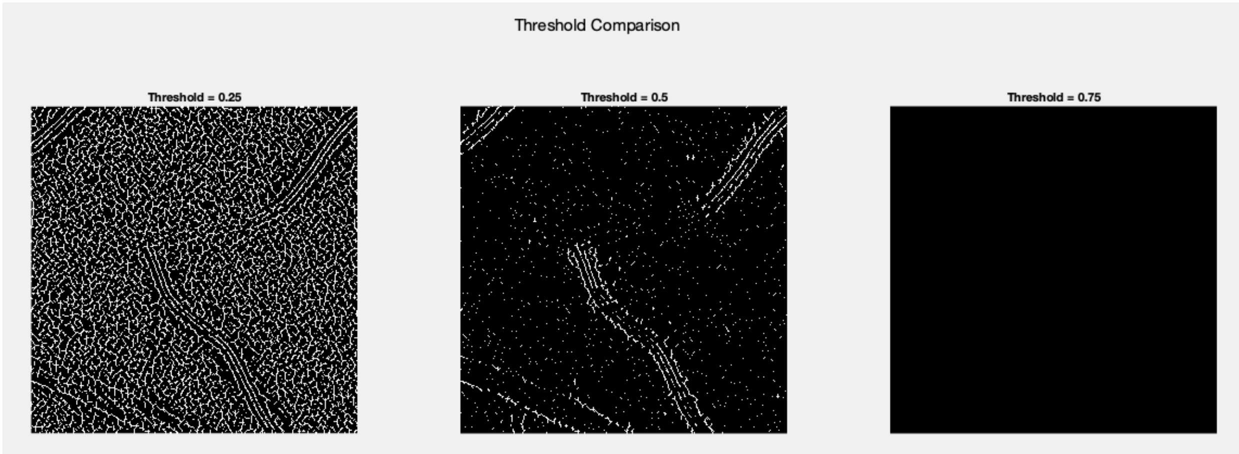

Figure 13: Threshold comparison for healthy subject filtered with a sobel filter and with a 7x7 non maxima suppression window size

As you increase the threshold, you increase the number of pixels that will make it through the filter. This means that there is an ideal balance between too high of a threshold and too low. As we can see in the example, the threshold of 0.75 was far too high, and the threshold of 0.25 was far too low. The best result was 0.5, although that could be lowered slightly as some vessels are missing.

2.4 Vessel Segmentation

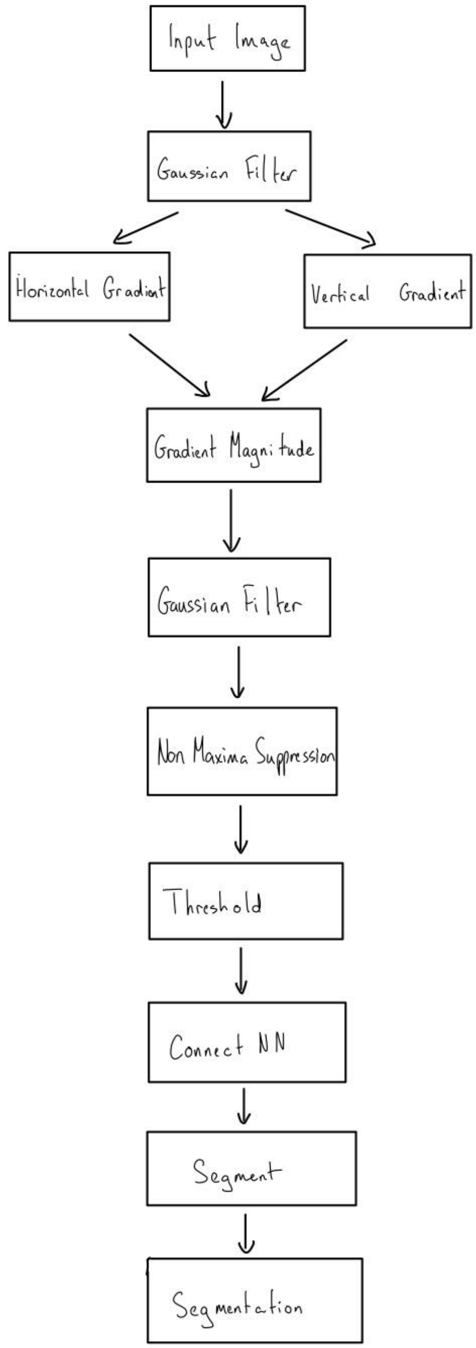

Figure 14: Vessel segmentation pipeline

Block Diagram Explanation:

1. **Gaussian Filter -** This is used as a blurring filter. An essential step to ensure any unwanted noise doesn't get sharpened/amplified later in the process.
2. **Gradient Magnitude -** The gradient magnitude filters are used to amplify the edges within the image. This is important because it allows the segmentation to identify more easily the edges of the vessels.

3. **Non Maxima Suppression -** This is used to thin the edges, so that only the true edges are shown.
4. **Threshold -** This block compares each pixels value with a threshold and sets those pixels that are above to equal one
5. **Connect NN -** This block scans the 5x5 neighbourhood around the pixel in question to see if any of the other pixels equals 1. It then connects the nearest pixel to the one in question with a line

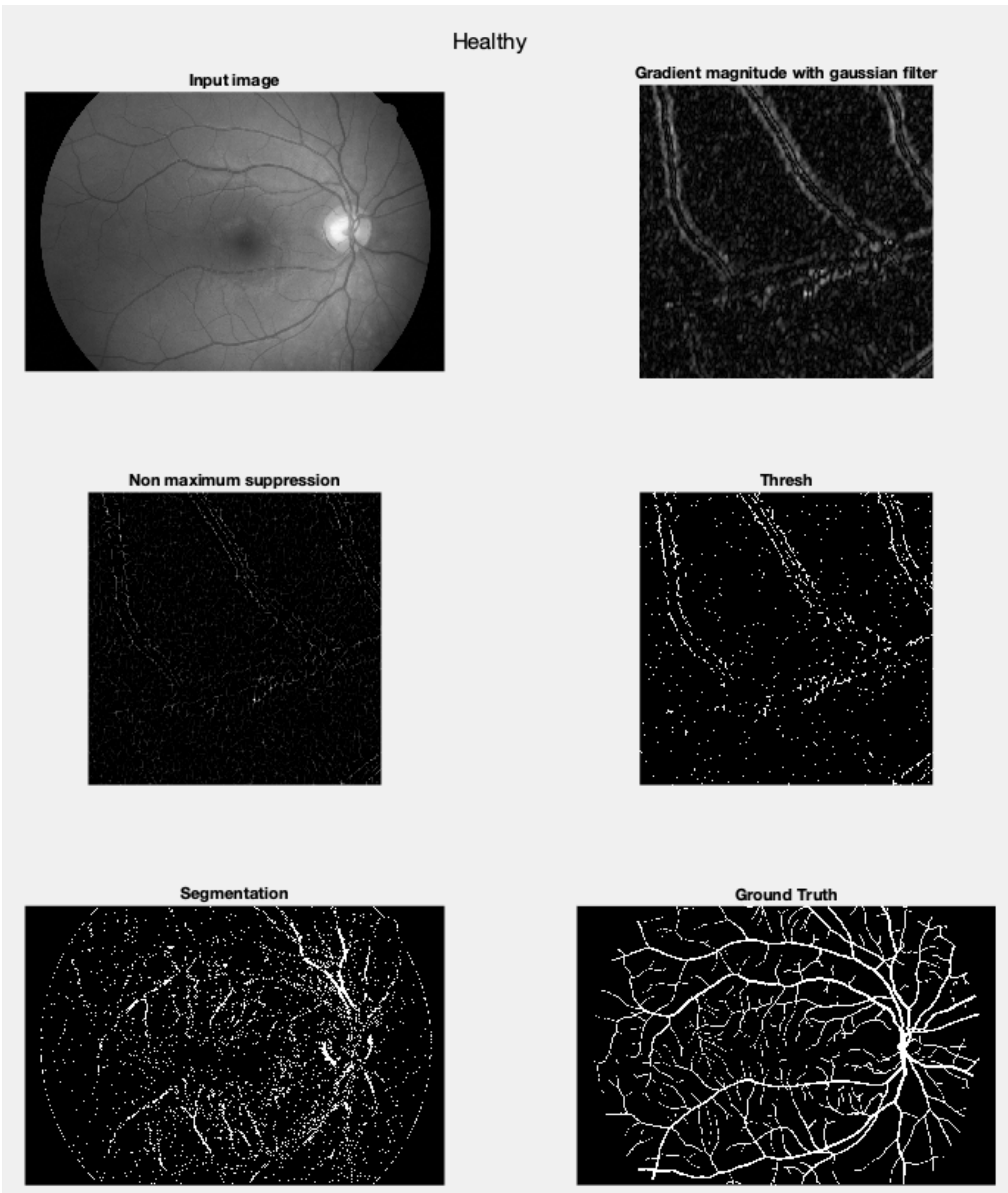

Figure 15: Healthy subject vessel segmentation pipeline sobel gradient filter, 3x7 non maxima suppression window size and DSC 0.4962

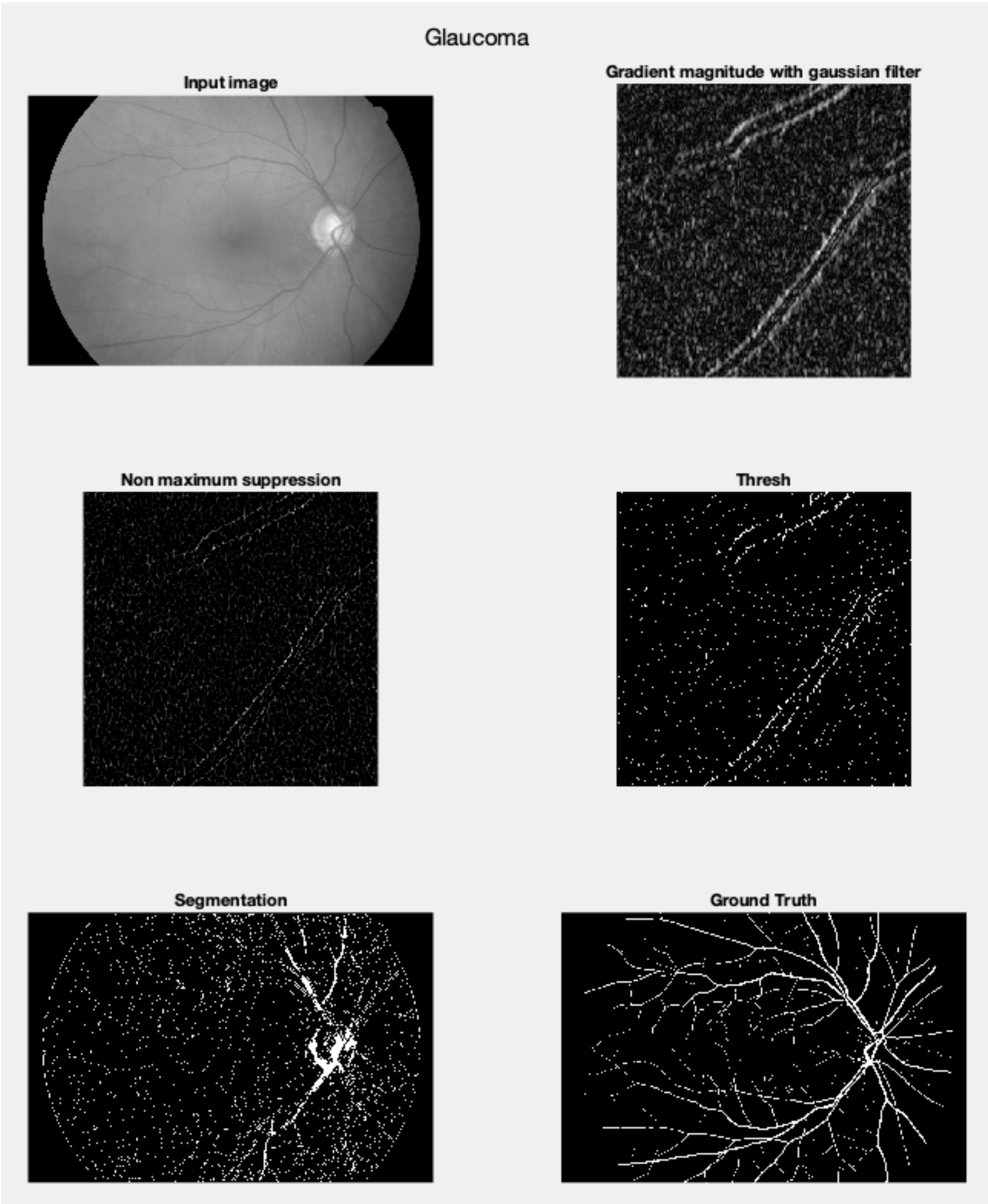

Figure 16: Glaucoma subject vessel segmentation pipeline sobel gradient filter, 3x7 non maxima suppression window size and DSC 0.4184

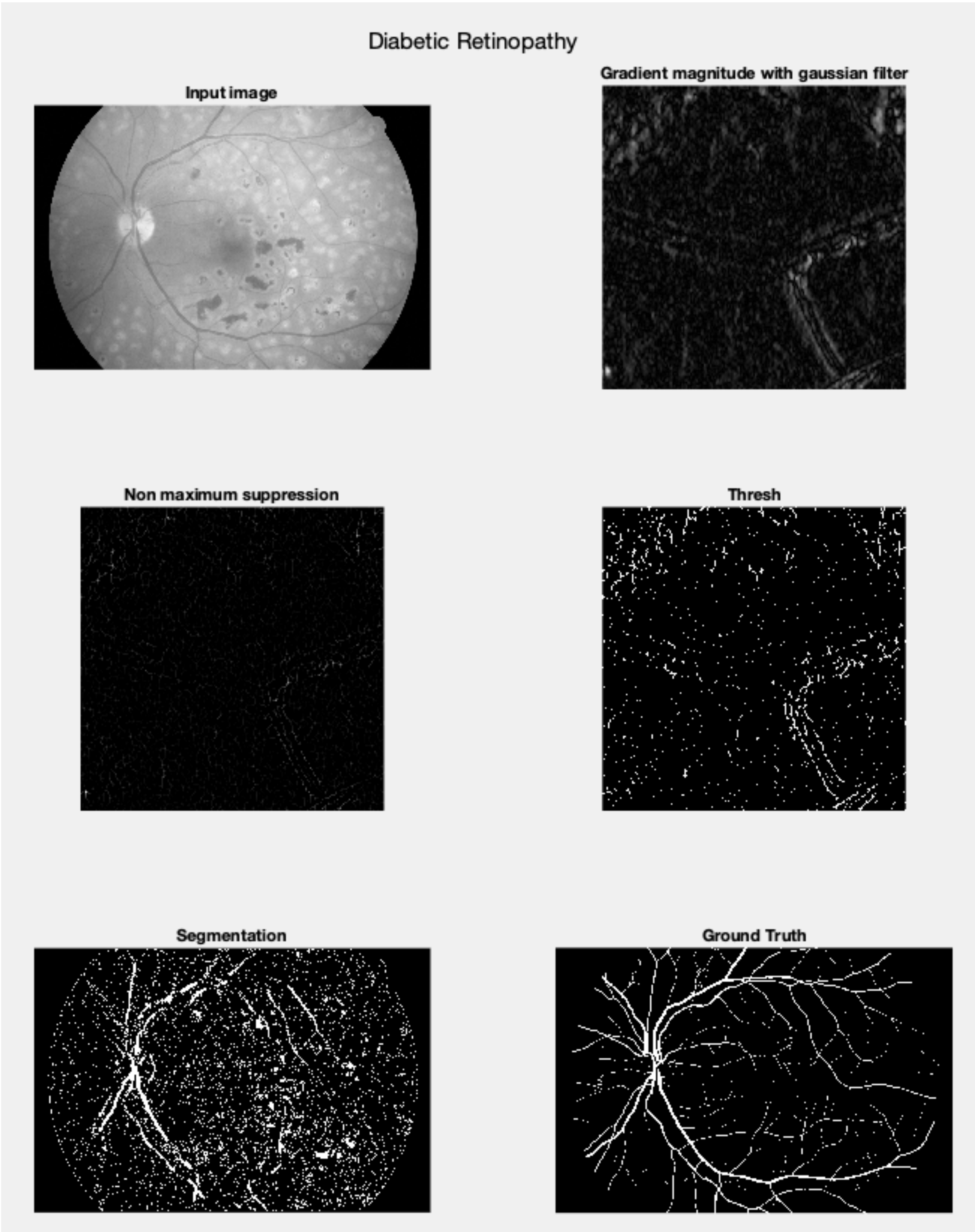

Figure 17: Diabetic retinopathy subject vessel segmentation pipeline sobel gradient filter, 3x7 non maxima suppression window size and DSC 0.6861

Figures 15-17 show the output of our vessel segmentation pipeline for three different subjects. There is a lot of noise present in all of the images that resulted in a lot of extra pixels being labelled as blood vessels when they were not. This noise could possibly be filtered out by a median filter that could potentially improve the performance of the algorithm. The edge detected results for the abnormal images were worse. In the glaucoma subjects the edges weren't easily identified and more edges were missed while the diabetic retinopathy subjects have lots of lesions growing in the background that lead to the algorithm detecting those edges and not just the blood vessels. The edge information could be used to detect glaucoma by comparing the strength of the edges. If the edge strength is below a certain value than it could be classified as glaucoma or healthy if it is above the value.