Detecting Diabetic Retinopathy in Fundus Images using Image Processing

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Introduction:

Diabetes occurs due to the body's inability to properly produce necessary insulin to convert food into energy. If left uncontrolled, diabetes can lead to further chronic diseases such as diabetic retinopathy (DR). In DR, new blood vessels develop improperly and leak often, causing microaneurysms and hemorrhages as seen in Figure 1. With no early symptoms of the condition, it is hard to detect it in the first stages. Complications arise in the later stages of the disease and by this time, few preventative measures can be taken. This has led to an overall rise in DR over time as it is now the leading cause of blindness in American adults.

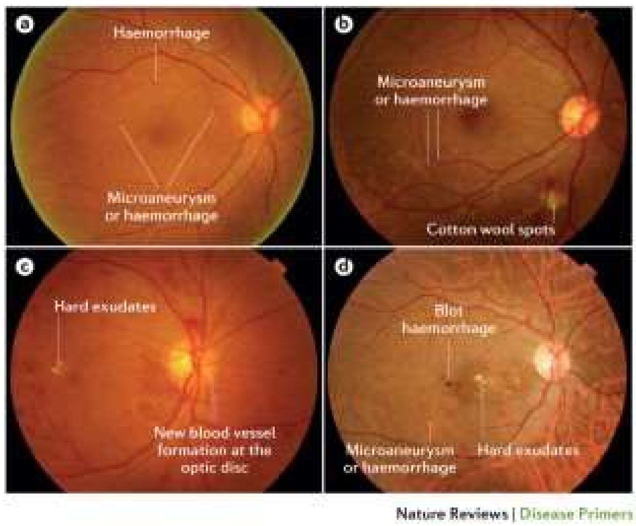

Figure 1: Fundus issues associated with DR
Citation: Wong, T., Cheung, C., Larsen, M. et al. Diabetic retinopathy. Nat Rev Dis Primers 2, 16012 (2016).
https://doi.org/10.1038/nrdp.2016.12 Figure 4: Clinical signs of diabetic retinopathy on fundoscopic examination.

Therefore, early detection of DR needs to be addressed to help prevent blindness from developing within communities worldwide. This can be addressed with a retinopathy study. Currently, DR diagnoses can only be performed by an ophthalmologist. However, with the aid of novel image processing algorithms, early DR can be detected without the need for specialists. This leads to the focus of this paper which is centered on detecting DR severity based on fundus images using image processing.

This project is important because it will function as an early medical intervention tool that can significantly reduce the incidence of vision loss while also mitigating the accessibility barrier. This pre-diagnosis tool can be used by anybody that can present a fundus image but would be most helpful in countries where there is a dearth of ophthalmologists.

This project focuses specifically on the classification of the severity of DR presented in fundus images. The images presented will be rated on a severity scale of 0-4, with 0 being the mildest nonproliferative level and 4 being the most severe proliferative level; this scale is like that of a clinician. Rating the fundus images on a DR scale of mild to severe using image processing can help someone decide if they should look for further medical care without the need to visit an ophthalmologist. This will significantly reduce the socioeconomic barriers associated with visiting an ophthalmologist as well as lower the instances of DR leading to blindness overall. This project proves that the process of identifying and diagnosing DR can be made significantly easier with the modern-day power of image processing algorithms.

Methodology:

This project would analyze images of retinas to detect the severity of DR present. It would include code to homogenize a given dataset of images by contrast and illumination and then segment anatomical features. The 6 steps of the pipeline are shown in Figure 2 and then further explained in this section.

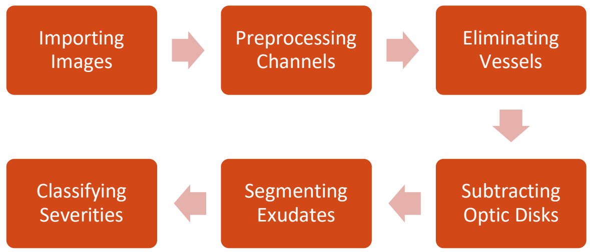

Figure 2: Project pipeline in 6 steps

Importing Images

The fundus images were obtained from Kaggle's 2015 Diabetic Retinopathy Detection Competition. Images were labeled with the subject's ID and then separated into "left" or "right." For this project, it was decided that most individuals upheld the same DR severity in both eyes. Thus, to simplify the dataset, it was decided to solely study the left images. A CSV file storing clinician ratings of DR severity for each image was also supplied to provide a means of ground truth comparison. The preliminary analysis showed an unequal distribution of DR severities with most results skewed towards the mild end of the spectrum. Moreover, a batch file testing mechanism was used to systematically evaluate the program on random folders consisting of 10 new images. Testing on 2 of each severity would make sure that the program was unbiased toward milder cases.

Preprocessing Channels

Since the images were obtained from a variety of instruments and environments, there needed to be a way to homogenize the images to prevent bias. Looking at a sample of the dataset, images varied across a range of contrast levels and illumination presets. To mitigate these discrepancies, a variety of functions were used. First, the original RGB images were converted to grayscale to focus solely on pixel intensities in one color channel. Then, the adapthisteq() was used to apply Contrast-Limited Adaptive Histogram Equalization (CLAHE). Compared to regular AHE, CLAHE performs a better job at keeping noise in images from also being amplified. Finally, a median filter was applied with medfilt2() because compared with others like Gaussian, it does a better job at reducing noise while not overly blurring the overall image.

Eliminating Vessels

This step of the pipeline focused on morphological operations to segment the vessels. Before continuing with those operations, however, the green channel of the original RGB fundus images had to be extracted. This color channel was used because the blood vessels have the best contrast in this display. Then, with both vertical and horizontal line structural elements, the image was dilated using imdilate(). The imerode() function was used in conjunction with a smaller disk structural element to remove intermittent patches. This was then converted to a binary image with imbinarize(); the complement of this binary image was then burned onto the original image to remove all vessels.

Subtracting Optic Disks

This step parallels the last step with its focus on morphological operations, but it involves solely a moderately sized disk-shaped structural element and another color channel. The red color channel was extracted to obtain the best illumination of the optic disk. The imclose() function helped to impose morphology with the structural element to construct the full optic disk. Like the earlier step, the binary mask was imposed on the original image to remove the optic disk.

Segmenting Exudates

This penultimate step involves creating one last binary mask that extracts all pixels above a threshold. A histogram of pixel intensities for various images of different severities showed a value of 175 would be best for segmenting exudates. The complement of this binary mask was subtracted from the original image. This final image was binarized to highlight areas where an exudate was found.

Classifying Severities

After looking at the number of threshold pixels across a range of severities, it was found that each consecutive severity level correlated to a difference of 100,000 pixels. The overall spread of the thresholded pixels and saw a range of 100,000 to 500,000 pixels and was divided this range amongst the 5 severities to classify the images.

Experiments and Results:

Initially, 10 images were evaluated and used to create the code. With consideration for the length of this report, only 5 of these 10 images are shown below in Figure 3. This figure shows 5 fundus images as they are run through each step in the pipeline. Figure 3b shows how the blemishes are much clearer after the original image has been preprocessed with filtration and contrast adjustment. The vessel's binary mask was applied to create Figure 3c. After the optic disk was detected, it was removed to create Figure 3d. Finally, Figure 3e shows the regions of the image after the exudate segmentation. Classification results from all 10 images, however, were used to compute the confusion matrix shown in Figure 4.

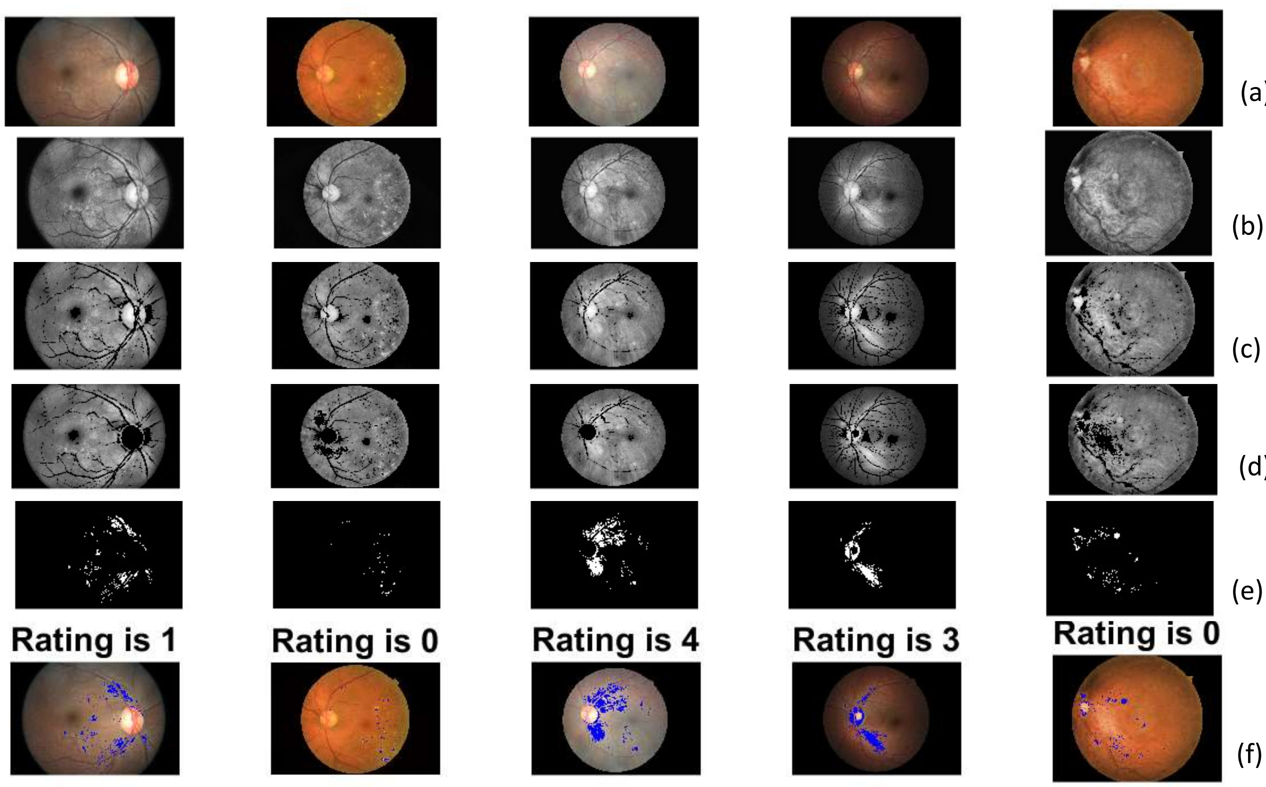

Figure 3: Fundus image output from the steps of the pipeline. (a) Importing images from the batch folder. (b) Preprocessing images with noise filtration and contrast adjustment. (c) Eliminating vessels with line morphology. (d) Subtracting optic disk with disk morphology. (e) Segmenting exudates with image thresholding. (f) Overlay exudate binary mask on RGB images and displaying classifier labels.

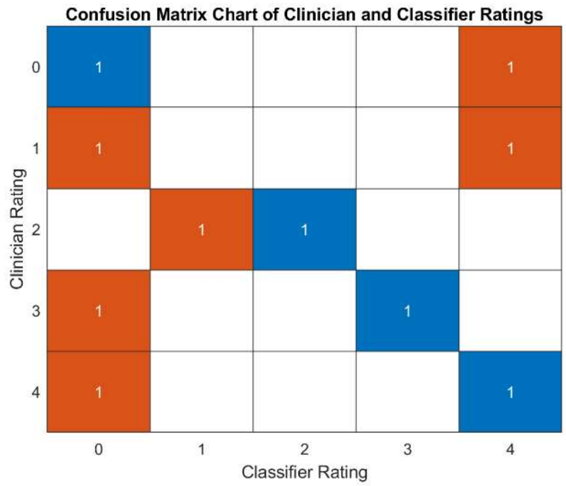

Figure 4: Confusion matrix of 10 fundus images

Discussion:

The pipeline discussed in the methodology section was successful for some of the images. As shown in the confusion matrix in Figure 4, the accuracy of the program can be assumed to be 40%. Most of these discrepancies occurred when the classifier detected more proliferative cases of DR as mild cases. This is an unfortunate conclusion as it is preferred to report false positives than false negatives. This may be due to various issues that came up while deciding the methodology and could be changed to improve the final accuracy.

Looking at a sample of the dataset initially, a huge variability of image appearances. The images from this dataset were taken using different instruments and were therefore inherently variant. It was later found while preprocessing that the assorted sizes and resolutions resulted in difficulty in deciding how to best homogenize them. Future improvements of this project could include a function dedicated to extracting solely the fundus part of the image and potentially cropping out the background. Moreover, detecting centroids across a range of images and overlapping them could homogenize the pixel area the program is seeing. Reshaping the images to crop only the fundus and scaling them to the same absolute dimensions would mitigate this variation issue.

Also, looking at the resulting outputs shown in Figure 3, there are many image processing techniques upon which significant improvement can be made. One of which is the technique for optic disk localization. As shown in Figure 3d, the segmentation for the optical disk bled outside of the anatomical region. The optic disk is circular, but the segmented images show larger areas as the disk including parts of the retina nearby. In the future, adjusting the contrast before this step and then clustering the brightest pixels would outline the optic disk better. An alternative route would be using the circular Hough transform through imfindcircles() to find centers and Sobel operators through edge() for detecting boundaries.

Overall, completing this project has taught the team a great deal about the intersection of healthcare and technology. The image processing techniques that were learned in this MATLAB course can be applied in many future careers. Regarding DR specifically, it is particularly important to try to advance image detection techniques like the ones applied in this project. With socio-economic barriers and lack of ophthalmologists, it is difficult for patients to get an early diagnosis for DR. Using this technology can lessen this burden and detect the disease in its earlier stages, saving lives.