A THESIS ON

Automatic Microaneurysms Extraction from Retinal Fundus Image to Detect Diabetic Retinopathy

This Thesis is Submitted in partial fulfillment of the requirements for the degree of Bachelor of Science in Electrical and Electronic Engineering

Course code: EEE-400 **Course Title:** Project/Thesis

Submitted By

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DEDICATED TO

OUR BELOVED PARENTS AND RESPECTABLE TEACHERS

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Abstract

Diabetes is a chronic end organ disease that occurs when the pancreas does not secrete enough insulin or the body is unable to process it properly. Over time, diabetes affects the circulatory system, including that of the retina. Diabetic retinopathy is a medical condition where the retina is damaged because fluid leaks from blood vessels into the retina. Ophthalmologists recognize diabetic retinopathy based on features, such as blood vessel area, exudes, hemorrhages, microaneurysms and texture on retinal fundus images. The images of retina are taken through either fundus photography. Fundus photography involves capturing a photograph of the back of the eye. Specialized fundus cameras that consist of a microscope attached to a flash enabled camera are used in fundus photography. Fundus images are then analyzed by ophthalmologists who look for certain patterns and defects in the image to predict diseases. There are many problems in this system. World is short of highly qualified ophthalmologists. Due to this people have to wait for long before starting medications. This sometimes worsens the condition. Another crucial disadvantage is lack of agreement between different doctors on a single profile of fundus. We have started with fundus images to analyze retina. Our project aims to analyze these defects through sophisticated image processing techniques, based on known patterns and defects. In this paper we extract Microaneurysm (MA) from fundus image. We have put our work in different sections. First, we have thoroughly explained all the major concepts of Diabetic and Diabetic related Diseases. In next section we have described the feature extraction procedures for blood vessels. In the last section we have discussed about our results and future sectors.

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Introduction

1.1 Diabetes:

Diabetes is a disease that affects the human body's ability to produce or use insulin. Insulin is a hormone. When the body turns the food, human eats into energy (also called sugar or glucose), insulin is released to help transport this energy to the cells. Insulin acts as a "key." Its chemical message tells the cell to open and receive glucose. If the human body produces little or no insulin or is insulin resistant, too much sugar remains in the blood. Blood glucose levels are higher than normal for individuals with diabetes. There are two main types of diabetes: Type 1 and Type 2. When someone is affected with Type 1 diabetes, his pancreas does not produce insulin. Type 1 diabetes, once called juvenile diabetes, is often diagnosed in children or teens. However, it can also occur in adults. This type accounts for 5-10 percent of people with diabetes. Type 2 diabetes occurs when the body does not produce enough insulin, or when the cells are unable to use insulin properly, which is called insulin resistance. Type 2 diabetes is commonly called "adult-onset diabetes" since it is diagnosed later in life, generally after the age of 45. It accounts for 90-95 percent of people with diabetes. In recent years, Type 2 diabetes has been diagnosed in younger people, including children, more frequently than in the past.

1.2 Causes:

Type 1 diabetes occurs when your immune system, the body's system for fighting infection, attacks and destroys the insulin-producing beta cells of the pancreas. Scientists think type 1 diabetes is caused by genes and environmental factors, such as viruses, that might trigger the disease. Type 2 diabetes the most common form of diabetes is caused by several factors, including lifestyle factors and genes.

1.3 Effects:

Diabetes affects the kidney, eyes, nerves and heart. In the following sections, we have discussed these affects briefly.

1.3.1 Diabetic nephropathy

Diabetic nephropathy (diabetic kidney disease) is kidney damage that results from having diabetes. Having high blood glucose levels due to diabetes can damage the part of the kidneys that filters the blood. The damaged filter becomes ‘leaky’ and lets protein into the urine. Dis play or advertising of any products on myDr.com.au should not be taken as an endorsement by a healthcare professional. For some people, diabetic nephropathy can progress to kidney failure. However, most people with diabetes do not develop kidney disease that progresses to kidney failure.

1.3.2 Diabetic cardiomyopathy

Diabetic cardiomyopathy is defined as ventricular dysfunction which occurs in diabetic patients independent of a recognized cause, such as coronary artery disease (CAD) or hypertension.

1.3.3 Diabetic neuropathy

Diabetic neuropathy is a type of nerve damage that can occur if someone has diabetes. High blood sugar can injure nerves throughout the body. Diabetic neuropathy most often damages nerves in your legs and feet. Depending on the affected nerves, symptoms of diabetic neuropathy can range from pain and numbness in your legs and feet to problems with the digestive system, urinary tract, blood vessels, and heart. Some people have mild symptoms. But for others, diabetic neuropathy can be quite painful and disabling.

1.3.4 Diabetic retinopathy

Diabetic retinopathy is a condition that occurs in people who have diabetes. It causes progressive damage to the retina, the light-sensitive lining at the back of the eye. Diabetic retinopathy is a serious sight-threatening. Diabetes interferes with the body's ability to use and store sugar (glucose). The disease is characterized by too much sugar in the blood, which can cause damage throughout the body, eyes also. Over time, diabetes damages the blood vessels in the retina. Diabetic retinopathy occurs when these tiny blood vessels leak blood and other fluids. This causes the retinal tissue to swell, resulting in cloudy or blurred vision. The condition usually affects both eyes. The longer a person has diabetes, the more likely they will develop diabetic retinopathy. If left untreated, diabetic retinopathy can cause blindness.

Types of diabetic retinopathy

DR can be broadly classified as no proliferative DR (NPDR) and proliferative DR (PDR). Depending on the presence of specific DR features, the stages can be identified. The following list describes three subclasses of NPDR as well as PDR

I. Mild NPDR:

At least one microaneurysm with or without the presence of retinal hemorrhages, hard exudates, cotton wool spots or venous loops. Approximately 40% of people with diabetes have at least mild signs of diabetic retinopathy.

II. Moderate NPDR:

Numerous microaneurysms and retinal hemorrhages are present. A limited amount and cotton wool spots of venous beading can also be seen 16% of the patients with moderate NPDR will develop PDR within 1 year.

III. Severe NPDR:

Is characterized by any one of the following (4-2-1 rule) characteristics: (1) numerous hemorrhages and microaneurysms in 4 quadrants of the retina (2) venous beading in 2 or more quadrants (3) Intraretinal microvascular abnormalities in at least 1 quadrant Severe NPDR carries a 50% chance of progression to PDR within 1 year.

IV. PDR:

Is the advanced stage; signals, sent by the retina for nourishment, trigger the growth of new blood vessels. These blood vessels do not cause symptoms or vision loss. But their walls are thin and fragile, this leads to a high risk that they leak blood. This leaked blood contaminates the vitreous gel and this causes severe vision loss and even blindness. About 3% of people, with this condition, may experience severe visual loss.

1.4. Literature Review:

Diabetic Retinopathy is an active research area. A lot of research has been done in last few years. Computer scientists and medical researchers have developed many algorithms for automatic detection of eye diseases, though accuracy has never been very great. Researchers have been trying new features and new algorithms to improve further. Joshi, et al. [1] have used morphological operations for image segmentation. Hussain et al. [2] have local variation operators and split and merge algorithm to detect fine exudates. Shraddha et al. [3] detected exudates by calculating differential morphological profile (DMP). This approach has very good specificity and PPV values as 99.99% and 98.23% respectively. Xu et al. [4] proposed a method to segment retinal blood vessels to overcome the variations in contrast of large and thin vessels. This method uses adaptive local thresholding to produce a binary image then extract large connected components as large vessels. The residual fragments in the binary image including some thin vessel segments (or pixels), are classified by Support Vector Machine (SVM). Gonzalez et al. [5] presented a method to segment blood vessels and optic disk in the fundus retinal images. The method takes as first step the extraction of the retina vascular tree using the graph cut technique. The blood vessel information is then used to estimate the location of the optic disk. The optic disk segmentation is performed using two alternative methods. The Markov random field (MRF) image reconstruction method segments the optic disk by removing vessels from the optic disk region, and the compensation factor method segments the optic disk using the prior local intensity knowledge of the vessels. R.M. Rangayyan et al. Al-Rawi et al. [6] used the matched filter response to the detection of blood vessels is increased by proposing better filter parameters. These filter parameters are found by using an optimization procedure on 20 retina images of the DRIVE database. Martinez-Pérez et al. [7] proposed a method based on multiscale analysis to obtain vessels widths, lengths and orientations information. The local maxima over scales of the magnitude of the gradient and the maximum principal curvature of the Hessian tensor are used in a multiple pass region growing procedure. The growth progressively segments the blood vessels using feature information together with spatial information. Many methods have been developed previously to detect microaneurysms. Year 1996, T. Spencer et al.[8] presented a strategy to identify MA's based morphology and matched filter. Many other authors extended the Spencer's approaches with different classification step. These methods are used to detect MAs from florescence angiograms. Year 2005, M. Niemeijer et al. [9]

has mixed the two strategies of Spencer et al. and Frame et al. along with a kNN classifier to detect MA candidates from fundus images. Year 2008, Gwenole Quellec et al. [10] proposed to use wavelet transform in detection process. Year 2014, the method of Shan Ding and Wenyi Ma [5] detects MA's using dynamic multi-parameter template matching (DMPT). Lama Seoud [11], contributed in finding a set of dynamic shape features for detection of MA.

Jorge Oliveira et al [12] presented Slant stacking, a formulation of the Radon transform, to automatically detect MAs. The Radon transform was applied to an MA candidate and a set of 21 features from the Radon domain were extracted. SVM classifier with RBF kernel was used and a 5 fold cross validation method was used to train the classifier. Luca Giancardo et al. [13] presented a technique for the detection of MA using Radon Transform for detecting single circular Gaussian like structures. Three properties namely location in the window, size and intensity of the circular Gaussian shape were studied from the Radon cliffs. The candidate was considered for further processing for path vote > 4 and then the probability of being a MA was calculated. L. Giancardo et al. [14] proposed a new MA segmentation technique based on a novel Radon based approach. The Radon Transform was applied to the normalized image to obtain the Radon space. The Radon space was analysed to separate the MAs from other dark structures such as vessels and noise. Principal Component Analysis (PCA) and SVM classifier were used to classify the new set of features obtained from the Radon space analysis. Tsuyoshi Inoue et al. [15] proposed detection of MA candidate by the use of Eigen values based on a Hessian matrix. The Eigen values were used to classify the shape of the intensity curve surface. A small shape index value indicated the possibility of MA. 126 features were extracted and then fed to ANN classifier to classify the candidate regions. Abhir Bhalerao et al. [16] employed a standard linear filtering and eigen image value analysis for MA detection.

1.5 Our Work:

Microaneurysm (MA) is the earliest symptom that appears in the retina of a DR affected person. They are small, dark red, circular dots resulting due to swellings in retinal capillaries. Microaneurysm diameter may range from 10 to 125 microns. As MA are first occurring symptom for DR, their detection of MA can help in the early detection of DR. In this paper we have described a method for the detection of MA using morphological techniques. Now For the detection of MA we also need to extract the blood vessels from the fundus image. In this paper we have also described a method for the extraction of blood vessels from fundus image.

So, it is very important to detect Microaneurysm (MA) in the field of DR. Microaneurysm occur as small dark round dots (~ 15 - 60 mm) on fundus images. They are small bulges developed on weak blood vessels and are earliest sign of DR.

The green channel of the image is extracted as it gives the best contrast between the microaneurysms and other bright parts like blood vessels. Now, image contrast is further stretched by applying adaptive histogram equalization (CLAHE). The image contrast is stretched by applying adaptive histogram equalization before using edge detection (Canny method) to detect the outlines of the image. The boundary is detected by filling up the holes and a disc-shaped structuring element (SE) of radius 6 is created with morphological opening operation (erosion and dilation). The edge detection image is then subtracted from the image with boundaries to obtain an image without boundaries. After that, the holes or gaps are filled, resulting in microaneurysms and other unwanted artifacts.

Now we need to extract the blood vessels for the further progress in the MA detection. We have used Alternate sequential Filtering (ASF) along with other image processing techniques to extract blood vessels. We worked on red channel of image and get it segmented. But the presence of hemorrhages and clots made it difficult. In our procedure we have extracted green channel of image because it has greater contrast. To further increase contrast we apply Contrast Limited Adaptive Histogram Equalization. Applying ASF on this image gives us another image with average intensity of each region applied over it. Later we subtract this image from output of CLAHE. This gives us an image which contains faint traces of blood vessels with optic disk and other things removed. We binarize this image with a threshold T and get blood vessels segmented. The final image also contains noise and some undesirable elements. Noise is removed by eroding the image. Undesirable elements are removed by taking into account the feature that only blood vessels are linear in shape.

The blood vessels which are detected using the above mentioned method are subtracted from the image of microaneurysms and artifacts

In the future, our goal is to detect diabetic retinopathy with the help of machine learning technique by creating a classifier for automatic detection. As abnormal blood vessels and MA are present in the affected fundus image, this abnormality is detected by the mentioned process.

Firstly, we will convert the images into numerical data for further machine learning process. Then we will feed the data into different models to detect diabetic retinopathy so that this system can provide an early warning of diabetic retinopathy automatically.

Methodology

Methodology of the project can be overseen as follows:

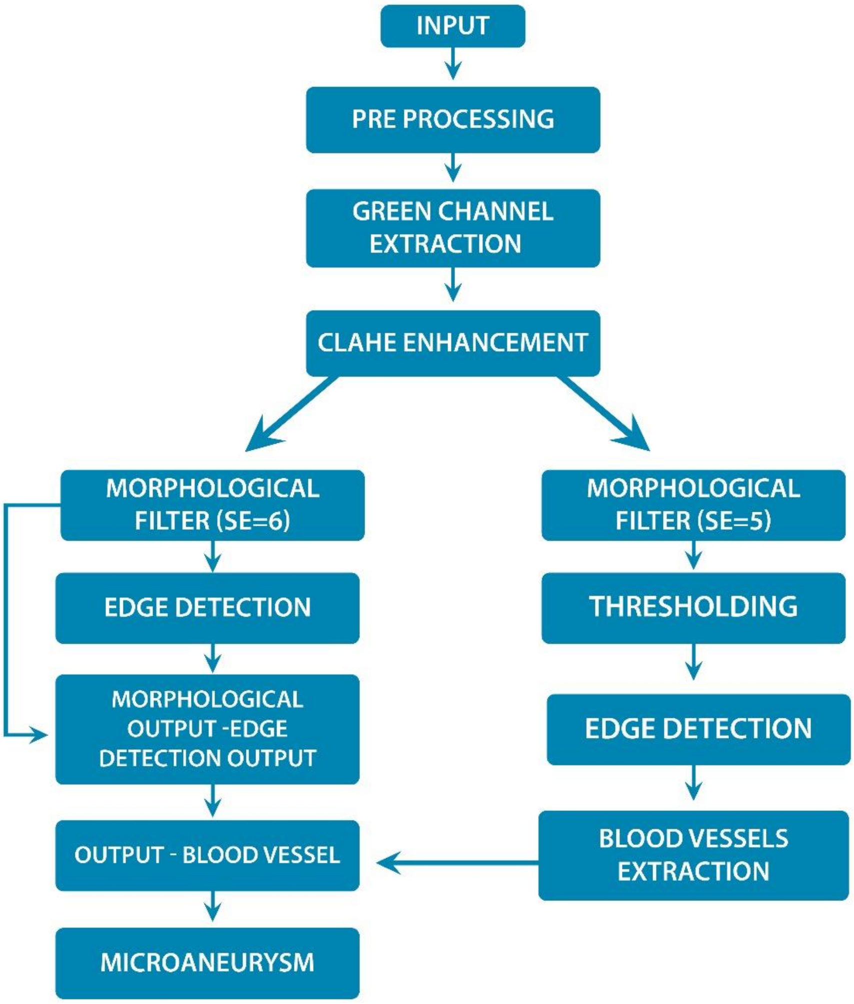


Figure 1: Block-diagram of overall process

2.1 Study of FUNDUS images:

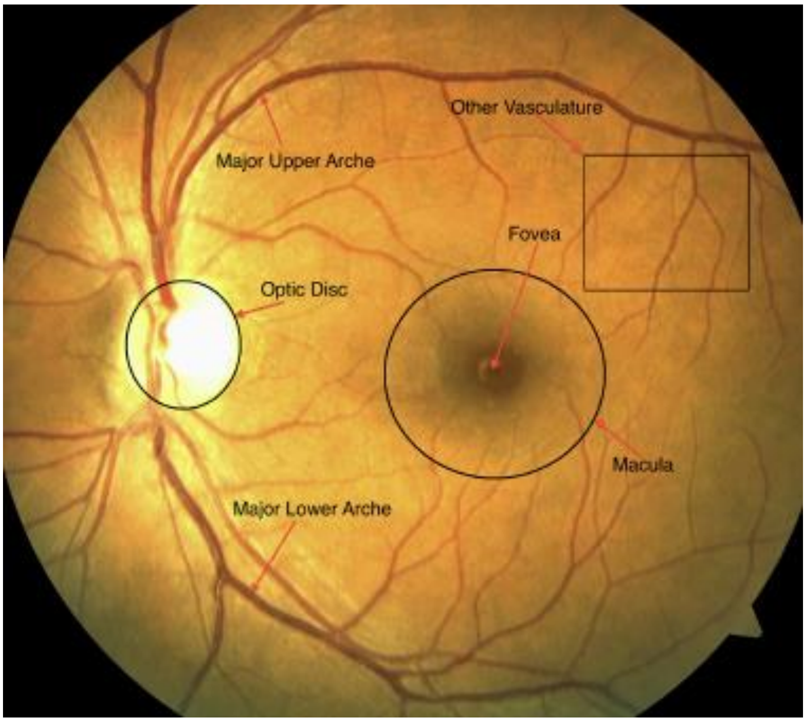


Figure 2: Fundus Image

Fundus photography involves photographing the rear of an eye; also known as the fundus. Specialized fundus cameras consisting of an intricate microscope attached to a flash-enabled camera are used in fundus photography. The main structures that can be visualized on a fundus photo are the central and peripheral retina, optic disc and macula. Fundus photography can be performed with colored filters, or with specialized dyes including fluorescein and indocyanine green. The optical design of fundus cameras is based on the principle of monocular indirect ophthalmoscopy. A fundus camera provides an upright, magnified view of the fundus. A typical camera views 30 to 50° of retinal area, with a magnification of 2.5x, and allows some modification of this relationship through zoom or auxiliary lenses from 15°, which provides 5x magnification, to 140° with a wide-angle lens, which minifies the image by half. The optics of a fundus camera are similar to those of an indirect ophthalmoscope in that the observation and illumination systems follow dissimilar paths.

The observation light is focused via a series of lenses through a doughnut-shaped aperture, which then passes through a central aperture to form an annulus, before passing through the camera objective lens and through the cornea onto the retina. The light reflected from the retina passes through the un-illuminated hole in the doughnut formed by the illumination system. As the light paths of the two systems are independent, there are minimal reflections of the light source captured in the formed image. The image forming rays continue towards the low powered telescopic eyepiece. When the button is pressed to take a picture, a mirror interrupts the path of the illumination system allow the light from the flashbulb to pass into the eye. Simultaneously, a mirror falls in front of the observation telescope, which redirects the light onto the capturing medium, whether it is a film or a digital CCD. Because of the eye's tendency to accommodate while looking through a telescope, it is imperative that the exiting vergence is parallel in order for an in-focus image to be formed on the capturing medium.

2.2 Channel Extraction:

Generally, there is higher contrast between vessel pixels and non-vassal pixels. That's why the green channel image contains more amount of information. Red light dominates the reflected spectrum as it gets less absorbed by the inner eye. That's why the fundus image is reddish. Red light has a lower co-efficient of absorption, that's is why pigments are less contrasted than green light. In the RGB-representation green channel shows the best contrast where red channel is often saturated and has low contrast. One other reason why Green channel is a better option that blue channel is very noisy and suffers from poor dynamic range than green channel. Blood containing elements (vessels) in the retinal layer are best represented and have highest contrast in the green channel.

2.3 Morphology:

The idea of the morphological filter is reduced and let grow process. The word "shrink" means using median filter to round off the large structures and to remove the small structures and in grow process, remaining structures are grown back by the same amount. The field of mathematical morphology contributes a wide range of operators to image processing, all based around a few simple mathematical concepts from set theory. The operators are particularly useful for the analysis of binary images and common usages include edge detection, noise removal, image enhancement and image segmentation. The two most basic operations in mathematical morphology are erosion and dilation. Both of these operators take two pieces of data as input: an image to be eroded or dilated, and a structuring element (also known as a kernel). The two pieces of input data are each treated as representing sets of coordinates in a way that is slightly different for binary and grayscale images. Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. According to Wikipedia, morphological operations rely only on the relative ordering of pixel values, not on their numerical values, and therefore are especially suited to the processing of binary images. Morphological operations can also be applied to greyscale images such that their light transfer functions are unknown and therefore their absolute pixel values are of no or minor interest. In morphological filter, each element in the matrix is called "structuring element" instead of coefficient matrix in the linear filter. The structuring elements contain only the value 0 and 1. And the hot spot of the filter is the dark shade element.

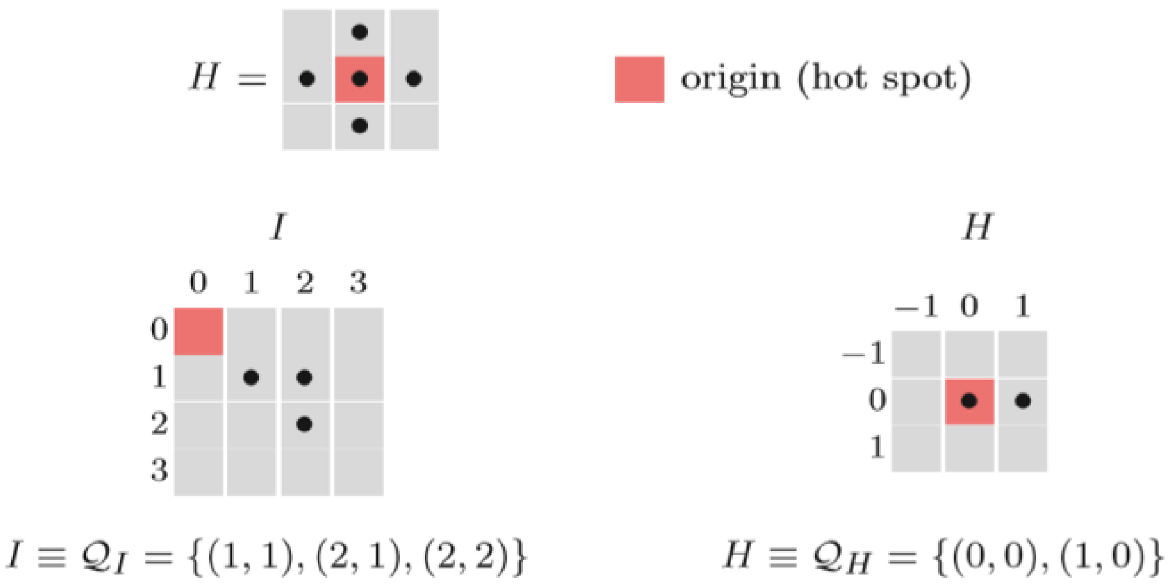


Figure 3: Structuring Element

The binary image is described as sets of two-dimensional coordinate point. This is called "Point Set" Q and point set consist of the coordinate pair p = (u,v) of all foreground pixels. Some operations of point set are similar to the operation in others image. For inverting binary image is complement operation and combining two binary image use union operators. Shifting binary image, I by some coordinate vector d by adding vector d to point p. Or reflection of binary image I by multiply -1 to point p.

For a binary image, white pixels are normally taken to represent foreground regions, while black pixels denote background. (Note that in some implementations this convention is reversed, and so it is very important to set up input images with the correct polarity for the implementation being used). Then the set of coordinates corresponding to that image is simply the set of two-dimensional Euclidean coordinates of all the foreground pixels in the image, with an origin normally taken in one of the corners so that all coordinates have positive elements.

For a grayscale image, the intensity value is taken to represent height above a base plane, so that the grayscale image represents a surface in three-dimensional Euclidean space. Figure 1 shows such a surface. Then the set of coordinates associated with this image surface is simply the set of three-dimensional Euclidean coordinates of all the points within this surface and also all points below the surface, down to the base plane. Note that even when we are only considering points with integer coordinates, this is a lot of points, so usually algorithms are employed that do not need to consider all the points Binary morphology can be seen as a special case of gray level morphology in which the input image has only two gray levels at values 0 and 1. Erosion and dilation work (at least conceptually) by translating the structuring element to various points in the input image, and examining the intersection between the translated kernel coordinates and the input image coordinates. For instance, in the case of erosion, the output coordinate set consists of just those points to which the origin of the structuring element can be translated, while the element still remains entirely `within' the input image. Virtually all other mathematical morphology operators can be defined in terms of combinations of erosion and dilation along with set operators such as intersection and union. Some of the more important are opening, closing and skeletonization.

Virtually all other mathematical morphology operators can be defined in terms of combinations of erosion and dilation along with set operators such as intersection and union. Some of the more important are opening, closing and skeletonization.

- ## Erosion

Erosion is one of the two basic operators in the area of mathematical morphology, the other being dilation. It is typically applied to binary images, but there are versions that work on grayscale images. The basic effect of the operator on a binary image is to erode away the boundaries of regions of foreground pixels (that is white pixels, typically). Thus, areas of foreground pixels shrink in size, and holes within those areas become larger. The erosion operator takes two pieces of data as inputs. The first is the image which is to be eroded. The second is a (usually small) set of coordinate points known as a structuring element (also known as a kernel). It is this structuring element that determines the precise effect of the erosion on the input image. The mathematical definition of erosion for binary images is as follows: Suppose that X is the set of Euclidean coordinates corresponding to the input binary image, and that K is the set of coordinates for the structuring element. Let Kx denote the translation of K so that its origin is at x. Then the erosion of X by K is simply the set of all points x such that Kx is a subset of X. The mathematical definition for grayscale erosion is identical except in the way in which the set of coordinates associated with the input image is derived. In addition, these coordinates are 3-D rather than 2-D. As an example of binary erosion, suppose that the structuring element is a 3×3 square, with the origin at its center as shown in Figure 1. Note that in this and subsequent diagrams, foreground pixels are represented by 1's and background pixels by 0's.

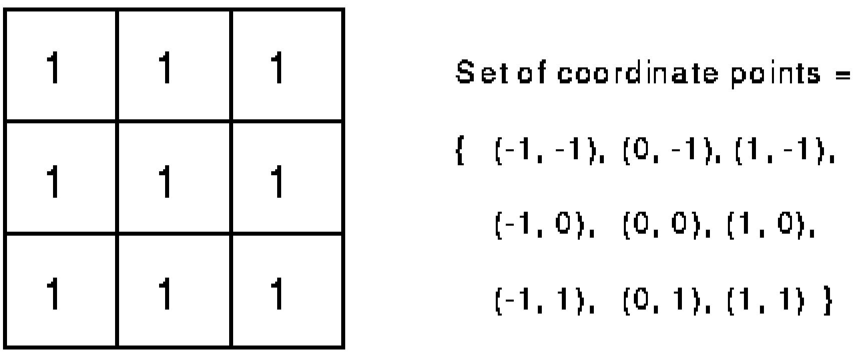


Figure 4: A 3×3 square structuring element

To compute the erosion of a binary input image by this structuring element, we consider each of the foreground pixels in the input image in turn. For each foreground pixel (which we will call the input pixel) we superimpose the structuring element on top of the input image so that the origin of the structuring element coincides with the input pixel coordinates. If for every pixel in the structuring element, the corresponding pixel in the image underneath is a foreground pixel, then the input pixel is left as it is. If any of the corresponding pixels in the image are background, however, the input pixel is also set to the background value. For our example 3×3 structuring element, the effect of this operation is to remove any foreground pixel that is not completely surrounded by other white pixels (assuming 8-connectedness). Such pixels must lie at the edges of white regions, and so the practical upshot is that foreground regions shrink (and holes inside a region grow). Erosion is the dual of dilation, that is eroding foreground pixels is equivalent to dilating the background pixels. Most implementations of this operator will expect the input image to be binary, usually with foreground pixels at intensity value 255, and background pixels at intensity value 0. Such an image can often be produced from a grayscale image using thresholding. It is important to check that the polarity of the input image is set up correctly for the erosion implementation being used. The structuring element may have to be supplied as a small binary image, or in a special matrix format, or it may simply be hardwired into the implementation, and not require specifying at all. In this latter case, a 3×3 square structuring element is normally assumed which gives the shrinking effect described above. The effect of erosion using this structuring element on a binary image is shown in Figure 2.

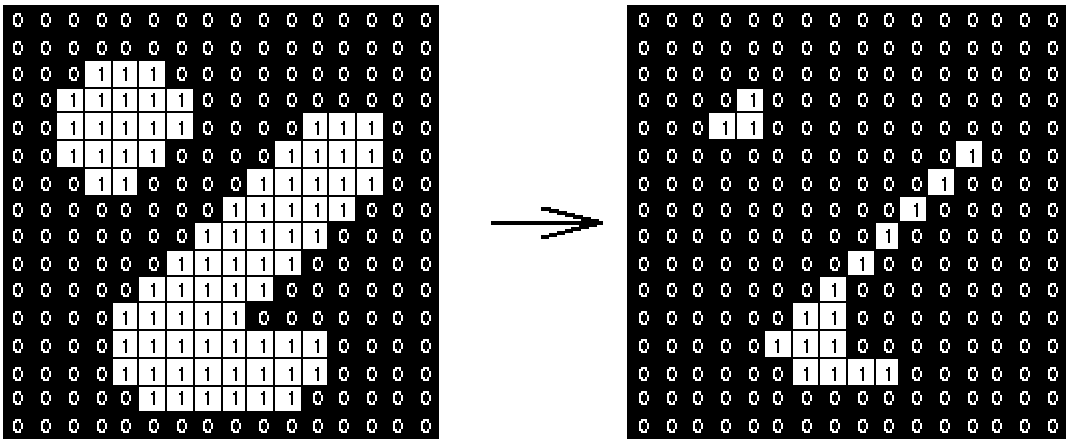


Figure 5: Effect of erosion using a 3×3 square structuring element

The 3×3 square is probably the most common structuring element used in erosion operations, but others can be used. A larger structuring element produces a more extreme erosion effect, although usually very similar effects can be achieved by repeated erosions using a smaller similarly shaped structuring element. With larger structuring elements, it is quite common to use an approximately disk-shaped structuring element, as opposed to a square one.

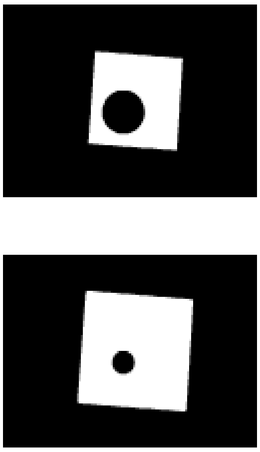


Figure 6: Effect of erosion

The image is the result of eroding four times with a disk-shaped structuring element 11 pixels in diameter. It shows that the hole in the middle of the image increases in size as the border shrinks. Note that the shape of the region has been quite well preserved due to the use of a disk-shaped structuring element. In general, erosion using a disk-shaped structuring element will tend to round concave boundaries, but will preserve the shape of convex boundaries.

Erosions can be made directional by using less symmetrical structuring elements. For example, a structuring element that is 10 pixels wide and 1-pixel high will erode in a horizontal direction only. Similarly, a 3×3 square structuring element with the origin in the middle of the top row rather than the center, will erode the bottom of a region more severely than the top.

Grayscale erosion with a flat disk-shaped structuring element will generally darken the image. Bright regions surrounded by dark regions shrink in size, and dark regions surrounded by bright regions grow in size. Small bright spots in images will disappear as they are eroded away down to the surrounding intensity value, and small dark spots will become larger spots. The effect is most marked at places in the image where the intensity changes rapidly, and regions of fairly uniform intensity will be left more or less unchanged except at their edges. Figure 3 shows a vertical cross-section through a gray level image and the effect of erosion using a disk-shaped structuring element. Note that the flat disk-shaped kernel causes small peaks in the image to disappear and valleys to become wider.

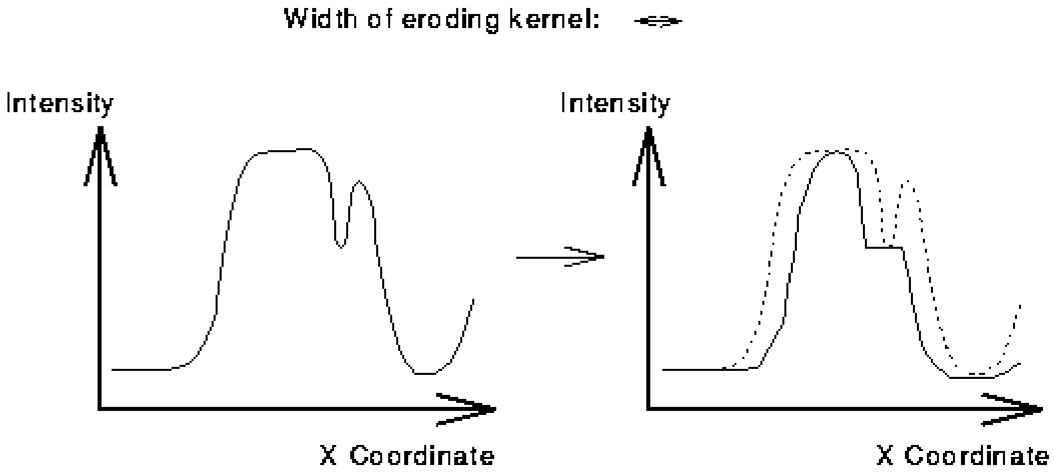


Figure 7: vertical cross-section through a gray level image

Figure 3 Gray level erosion using a disk-shaped structuring element. The graphs show a vertical cross-section through a gray level image.

- **Dilation**

Dilation is one of the two basic operators in the area of mathematical morphology, the other being erosion. It is typically applied to binary images, but there are versions that work on grayscale images. The basic effect of the operator on a binary image is to gradually enlarge the boundaries of regions of foreground pixels (that is white pixels, typically). Thus, areas of foreground pixels grow in size while holes within those regions become smaller. The dilation operator takes two pieces of data as inputs. The first is the image which is to be dilated. The second is a (usually small) set of coordinate points known as a structuring element (also known as a kernel). It is this structuring element that determines the precise effect of the dilation on the input image.

The mathematical definition of dilation for binary images is as follows:

Suppose that X is the set of Euclidean coordinates corresponding to the input binary image, and that

K is the set of coordinates for the structuring element.

Let Kx denote the translation of K so that its origin is at x.

Then the dilation of X by K is simply the set of all points x such that the intersection of Kx with X is non-empty.

The mathematical definition of grayscale dilation is identical except for the way in which the set of coordinates associated with the input image is derived. In addition, these coordinates are 3-D rather than 2-D.

As an example of binary dilation, suppose that the structuring element is a 3×3 square, with the origin at its center, as shown in Figure 1. Note that in this and subsequent diagrams, foreground pixels are represented by 1's and background pixels by 0's.

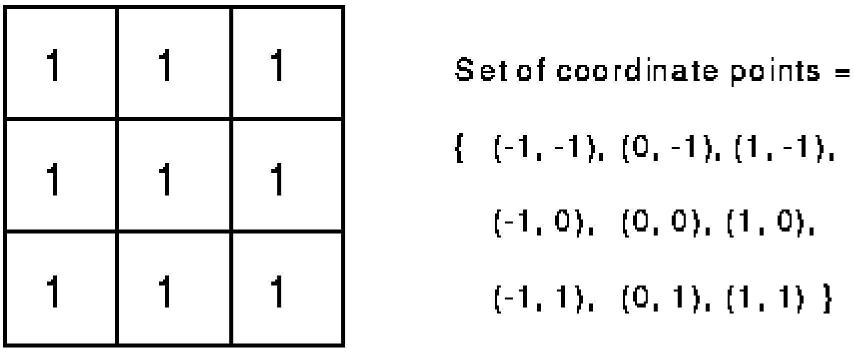


Figure 8: A 3×3 square structuring element

To compute the dilation of a binary input image by this structuring element, we consider each of the background pixels in the input image in turn. For each background pixel (which we will call the input pixel) we superimpose the structuring element on top of the input image so that the origin of the structuring element coincides with the input pixel position. If at least one pixel in the structuring element coincides with a foreground pixel in the image underneath, then the input pixel is set to the foreground value. If all the corresponding pixels in the image are background, however, the input pixel is left at the background value. For our example 3×3 structuring element, the effect of this operation is to set to the foreground color any background pixels that have a neighboring foreground pixel (assuming 8-connectedness). Such pixels must lie at the edges of white regions, and so the practical upshot is that foreground regions grow (and holes inside a region shrink). Dilation is the dual of erosion that is dilating foreground pixels is equivalent to eroding the background pixels. Most implementations of this operator expect the input image to be binary, usually with foreground pixels at pixel value 255, and background pixels at pixel value 0. Such an image can often be produced from a grayscale image using thresholding. It is important to check that the polarity of the input image is set up correctly for the dilation implementation being used. The structuring element may have to be supplied as a small binary image, or in a special matrix format, or it may simply be hardwired into the implementation, and not require specifying at all. In this latter case, a 3×3 square structuring element is normally assumed which gives the expansion effect described above. The effect of a dilation using this structuring element on a binary image is shown in Figure 2.

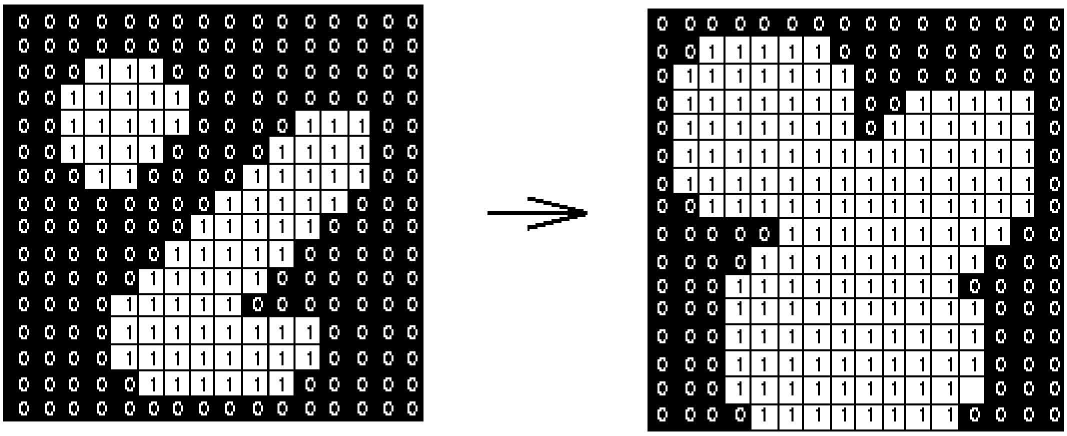
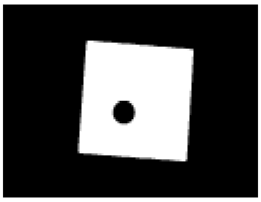
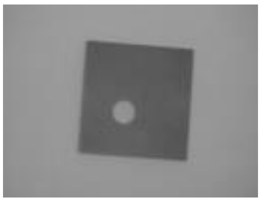


Figure 9: Effect of dilation using a 3×3 square structuring element

The 3×3 square is probably the most common structuring element used in dilation operations, but others can be used. A larger structuring element produces a more extreme dilation effect, although usually very similar effects can be achieved by repeated dilations using a smaller but similarly shaped structuring element. With larger structuring elements, it is quite common to use an approximately disk-shaped structuring element, as opposed to a square one. The image shows a thresholder image of





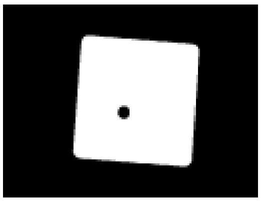


Figure 10: The basic effect of dilation on the binary

This image was produced by two dilation passes using a disk-shaped structuring element of 11 pixels radius. Note that the corners have been rounded off. In general, when dilating by a disk-shaped structuring element, convex boundaries will become rounded, and concave boundaries will be preserved as they are. Dilations can be made directional by using less symmetrical structuring elements. e.g. a structuring element that is 10 pixels wide and 1-pixel high will dilate in a horizontal direction only. Similarly, a 3×3 square structuring element with the origin in the middle of the top row rather than the center, will dilate the bottom of a region more strongly than the top. Grayscale dilation with a flat disk-shaped structuring element will generally brighten the image. Bright regions surrounded by dark regions grow in size, and dark regions surrounded by bright regions shrink in size. Small dark spots in images will disappear as they are `filled in' to the surrounding intensity value. Small bright spots will become larger spots. The effect is most marked at places in the image where the intensity changes rapidly and regions of fairly uniform intensity will be largely unchanged except at their edges. Figure 3 shows a vertical cross-section through a gray level image and the effect of dilation using a disk-shaped structuring element.

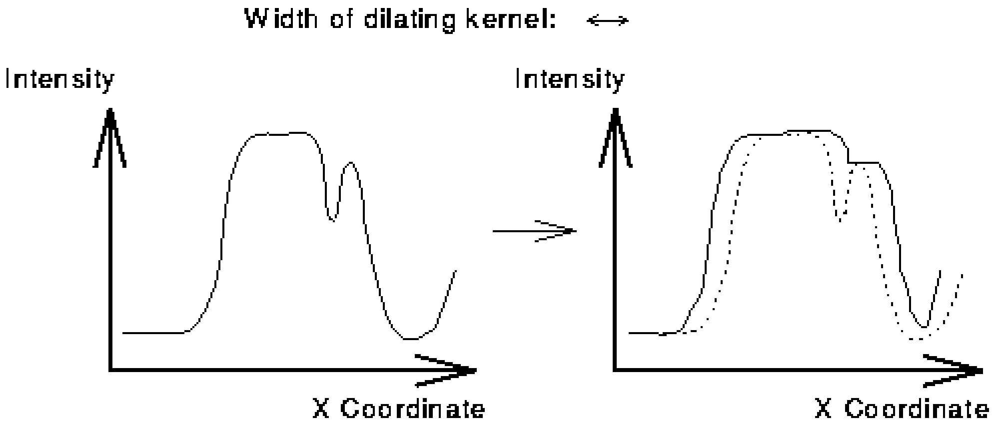


Figure 11: vertical cross-section through a gray level image

Figure 3 Gray level dilation using a disk-shaped structuring element. The graphs show a vertical cross-section through a gray level image.

- **Opening**

Opening and closing are two important operators from mathematical morphology. They are both derived from the fundamental operations of erosion and dilation. Like those operators, they are normally applied to binary images, although there are also gray level versions. 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. However, it is less destructive than erosion in general. 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. Very simply, an opening is defined as an erosion followed by dilation using the same structuring element for both operations. See the sections on erosion and dilation for details of the individual steps. The opening operator, therefore, requires two inputs: an image to be opened, and a structuring element. The gray level opening consists simply of a gray level erosion followed by a gray level dilation. Opening is the dual of closing, that is opening the foreground pixels with a particular structuring element is equivalent to closing the background pixels with the same element.

While erosion can be used to eliminate small clumps of undesirable foreground pixels, e.g. salt noise', quite effectively, it has the big disadvantage that it will affect all regions of foreground pixels indiscriminately. The opening gets around this by performing both erosion and dilation on the image. The effect of opening can be quite easily visualized. Imagine taking the structuring element and sliding it around inside each foreground region, without changing its orientation. All pixels which can be covered by the structuring element with the structuring element being entirely within the foreground region will be preserved. However, all foreground pixels which cannot be reached by the structuring element without parts of it moving out of the foreground region will be eroded away. After the opening

has been carried out, the new boundaries of foreground regions will all be such that the structuring element fits inside them, and so further openings with the same element have no effect. The property is known as idempotence. The effect of an opening on a binary image using a 3×3 square structuring element is illustrated in Figure 7.

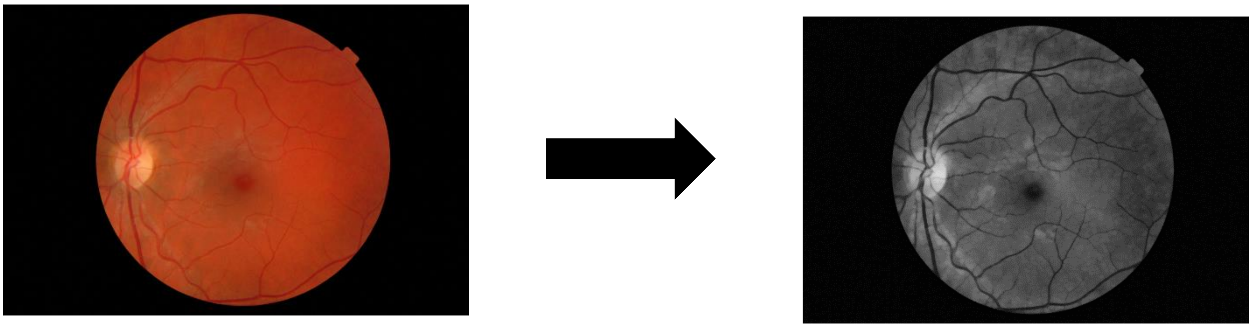


Figure 12: Effect of opening using structuring element

As with erosion and dilation, it is very common to use this 3×3 structuring element. The effect in the above figure is rather subtle since the structuring element is quite compact and so it fits into the foreground boundaries quite well even before the opening operation. To increase the effect, multiple erosions are often performed with this element followed by the same number of dilations. This effectively performs an opening with a larger square structuring element.

- **Closing**

Closing is an important operator from the field of mathematical morphology. Like its dual operator opening, it can be derived from the fundamental operations of erosion and dilation. Like those operators, it is normally applied to binary images, although there are gray level versions. Closing is similar in some ways to dilation in that it tends to enlarge the boundaries of foreground (bright) regions in an image (and shrink background color holes in such regions), but it is less destructive of the original boundary shape. As with other morphological operators, the exact operation is determined by a structuring element. The effect of the operator is to preserve background regions that have a similar shape to this structuring element, or that can completely contain the structuring element while eliminating all other regions of background pixels.

Closing is opening performed in reverse. It is defined simply as a dilation followed by an erosion using the same structuring element for both operations. See the sections on erosion and dilation for details of the individual steps. The closing operator, therefore, requires two inputs: an image to be closed and a structuring element. Gray level closing consists straightforwardly of a gray level dilation followed by a gray level erosion.

Closing is the dual of opening, that is closing the foreground pixels with a particular structuring element, is equivalent to closing the background with the same element. One of the uses of dilation is to fill in small background color holes in images, e.g. `pepper noise'. One of the problems with doing this, however, is that the dilation will also distort all regions of pixels indiscriminately. By performing an erosion on the image after the dilation, that is closing, we reduce some of this effect. The effect of closing can be quite easily visualized. Imagine taking the structuring element and sliding it around outside each foreground region, without changing its orientation. For any background boundary point, if the structuring element can be made to touch that point, without any part of the element is inside a foreground region, then that point remains background. If this is not possible, then the pixel is set to the foreground. After the closing has been carried out the background region will be such that the structuring element can be made to cover any point in the background without any part of it also covering a foreground point, and so further closings will have no effect. This property is known as idempotence. The effect of closing on a binary image using a 3×3 square structuring element is illustrated in Figure 1.

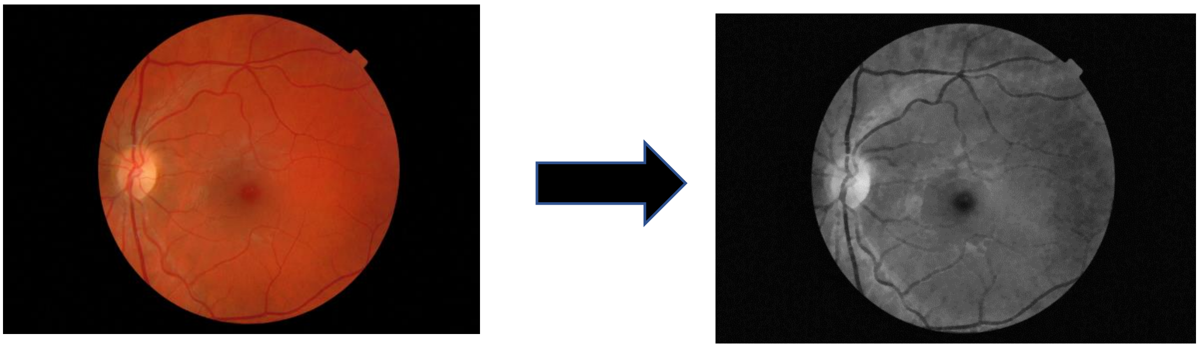


Figure 13: Effect of Closing using structuring element

As with erosion and dilation, this particular 3×3 structuring element is the most commonly used, and in fact many implementations will have it hardwired into their code, in which case it is obviously not necessary to specify a separate structuring element. To achieve the effect of a closing with a larger structuring element, it is possible to perform multiple dilations followed by the same number of erosions.

Closing can sometimes be used to selectively fill in particular background regions of an image. Whether or not this can be done depends upon whether a suitable structuring element can be found that fits well inside regions that are to be preserved, but doesn't fit inside regions that are to be removed.

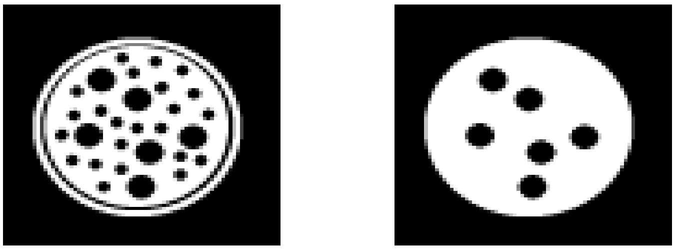


Figure 14: closing with a disk-shaped structuring element

The first image is an image containing large holes and small holes. If it is desired to remove the small holes while retaining the large holes, then we can simply perform a closing with a disk-shaped structuring element with a diameter larger than the smaller holes, but smaller than the large holes. The second image is the result of a closing with a 22-pixel diameter disk. Note that the thin black ring has also been filled in as a result of the closing operation.

2.4 Thresholding:

Thresholding is useful to remove unnecessary details from an image to concentrate on essentials. In the case of Fundus images, by removing all gray level information, the blood vessels are reduced to binary pixels. It is necessary to distinguish blood vessels foreground from the background information. Thresholding can also be used to bring out hidden details. It is very useful in the image region, which is obscured by similar gray levels. Therefore, choosing an appropriate threshold value is important, because a low value may decrease the size of some of the objects or reduce the number of these objects and a high value may include extra background information. Thresholding helps us in converting image's features into numerical data which is then applied on various machine learning algorithms as finding binary values in images is easy. This provides as a channel to convert fundus images into numerical values. There are various thresholding algorithms such as OTSU, adaptive, etc.

2.5 Edge Detection:

Canny method is used for edge detection. The Canny method performs better than the other edge detection methods, because it uses two thresholds to detect strong and weak edges, and for this reason, Canny algorithm is chosen for edge detection in the proposed technique.

Canny edge detection is a technique to extract useful structural information from different vision objects and dramatically reduce the amount of data to be processed. It has been widely applied in various computer vision systems. Canny has found that the requirements for the application of edge detection on diverse vision systems are relatively similar. Thus, an edge detection solution to address these requirements can be implemented in a wide range of situations. The general criteria for edge detection include:

1. Detection of edge with a low error rate, which means that the detection should accurately catch

as many edges shown in the image as possible.

2. The edge point detected from the operator should accurately localize on the center of the edge.

3. A given edge in the image should only be marked once, and where possible, image noise should not create false edges.

The Process of the Canny edge detection algorithm can be broken down to 5 different steps:

1. Apply Gaussian filter to smooth the image in order to remove the noise.
2. Find the intensity gradients of the image.
3. Apply non-maximum suppression to get rid of spurious response to edge detection.
4. Apply double threshold to determine potential edges.
5. Track edge by hysteresis: Finalize the detection of edges by suppressing all the other edges that are weak and not connected to strong edges.

2.6 Adaptive Histogram Equalization:

Histogram equalization usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values. A disadvantage of the method is that it is indiscriminate. It may increase the contrast of background noise while decreasing the usable signal. Adaptive histogram equalization (AHE) is a computer image processing technique used to improve contrast in images locally. It differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast and enhancing the definitions of edges in each region of an image. While performing AHE if the region being processed has a relatively small intensity range then the noise in that region gets more enhanced. It can also cause some kind of artifacts to appear in those regions. To limit the appearance of such artifacts and noise, a modification of AHE called CLAHE can be used. The amount of contrast enhancement for some intensity is directly proportional to the slope of the CDF function at that intensity level. Hence contrast enhancement can be limited by limiting the slope of the CDF. The slope of CDF at a bin location is determined by the height of the histogram for that bin. Therefore, if we limit the height of the histogram to a certain level, we can limit the slope of the CDF and hence the amount of contrast enhancement. The only difference between regular AHE and CLAHE is that there is one extra step to clip the histogram before the computation of its CDF as the mapping function is performed. Following is the overview of the algorithm for this function:

1. Calculation of a grid size based on the maximum dimension of the image. The minimum grid size is 32 pixels square.

2. If a window size is not specified chose the grid size as the default window size.

3. Identify grid points on the image, starting from top-left corner. Each grid point is separated by grid size pixels.

4. For each grid point calculate the histogram of the region around it, having area equal to window size and centered at the grid point.

5. If a clipping level is specified clip the histogram computed above to that level and then use the new histogram to calculate the CDF.

6. After calculating the mappings for each grid point, repeat steps 6 to 8 for each pixel in the input image.

7. For each pixel find the four closest neighboring grid points that surround that pixel.

8. Using the intensity value of the pixel as an index, find its mapping at the four grid points based on their cdfs.

9. Interpolate among these values to get the mapping at the current pixel location. Map this intensity to the range [min:max) and put it in the output image

Clipping the histogram itself is not quite straight forward because the excess after clipping has to be redistributed among the other bins, which might increase the level of the clipped histogram. Hence the clipping should be performed at a level lower than the specified clip level so that after redistribution the maximum histogram level is equal to the clip level. The CLAHE algorithm partitions the images into contextual regions and applies the histogram equalization to each one. This evens out the distribution of used grey values and thus makes hidden features of the image more visible.

Result

The result has been shown in the form of following steps

Pre-Processing:

In the pre-processing step we refine and filter the raw fundus image for better output. We refine and filter the images by the following characteristics.

Hue:

Hue is defined as the ratio of the green value to the red value of the pixel under discussion.
The supplied images may exhibit different brightness and Hues. The images are normalized so that the resulting image presents the same bulk-average (gross-average) hue. In the following figure we have shown the output of normalized hue from raw fundus images

Input **Output** **Input** **Output**

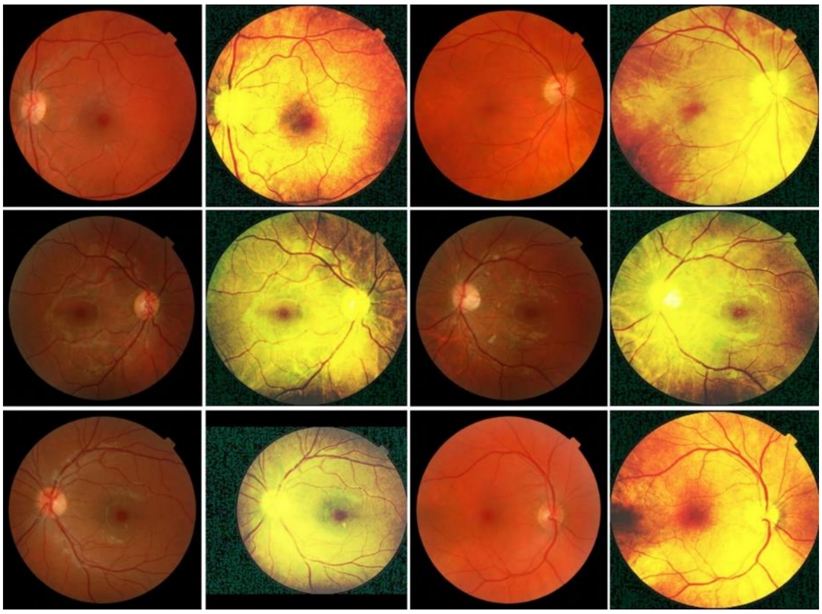


Figure 15: Filtering by hue

Contrast:

Contrast is the difference in luminance or color that makes an object distinguishable. In visual perception of the real world, contrast is determined by the difference in the color and brightness of the object and other objects within the same field of view. The contrast level of raw fundus images varies so we normalize the images in basis of an universal contrast. In the following figure we have shown the output of fixed contrast from raw fundus images.

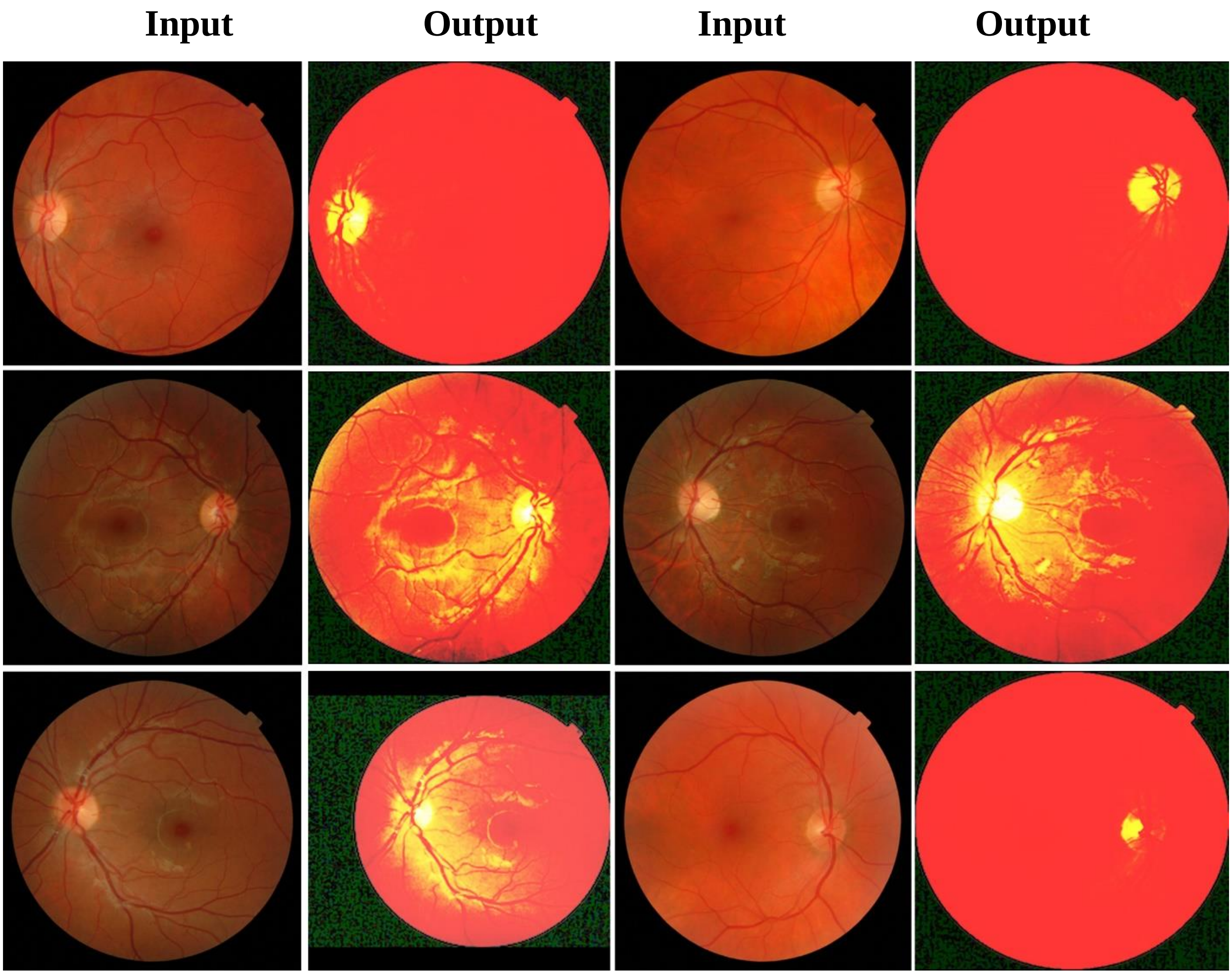


Figure 16: Filtering by Contrast

Stretching:

Contrast stretching is an image enhancement technique that attempts to improve the contrast in an image by `stretching' the range of intensity values it contains to span a desired range of values. In the following figure we have shown the output of fundus images of improved contrast by stretching.

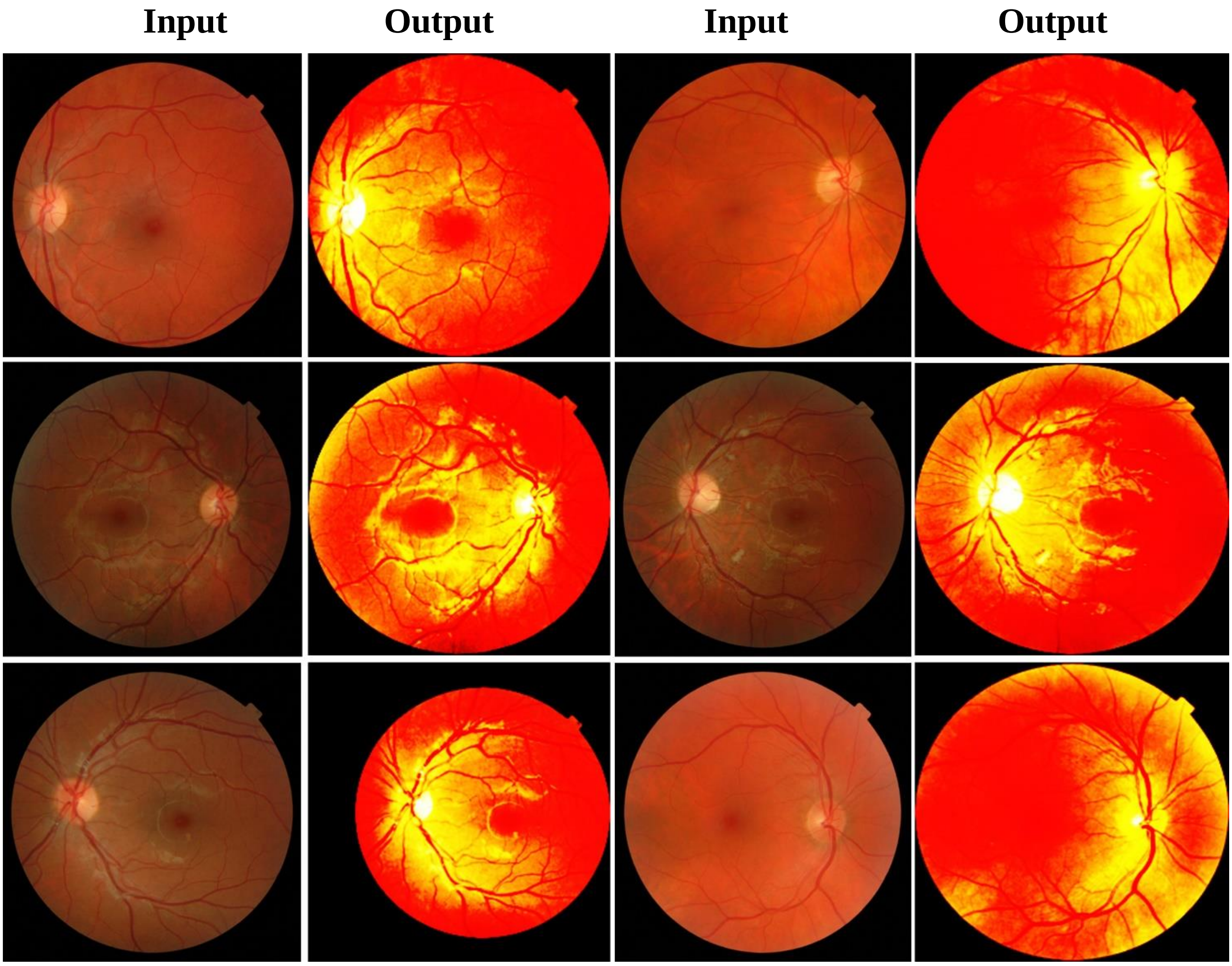


Figure 17: Filtering by Stretching

Saturation:

The RGB color representation has some drawbacks: components are strongly correlated, lack of human interpretation, nonuniformity, etc. A polar representation with the variable's luminance, saturation et hue(lum/sat/hue) allows us to solve these problems. In the following figure we have fixed the saturation of fundus image.

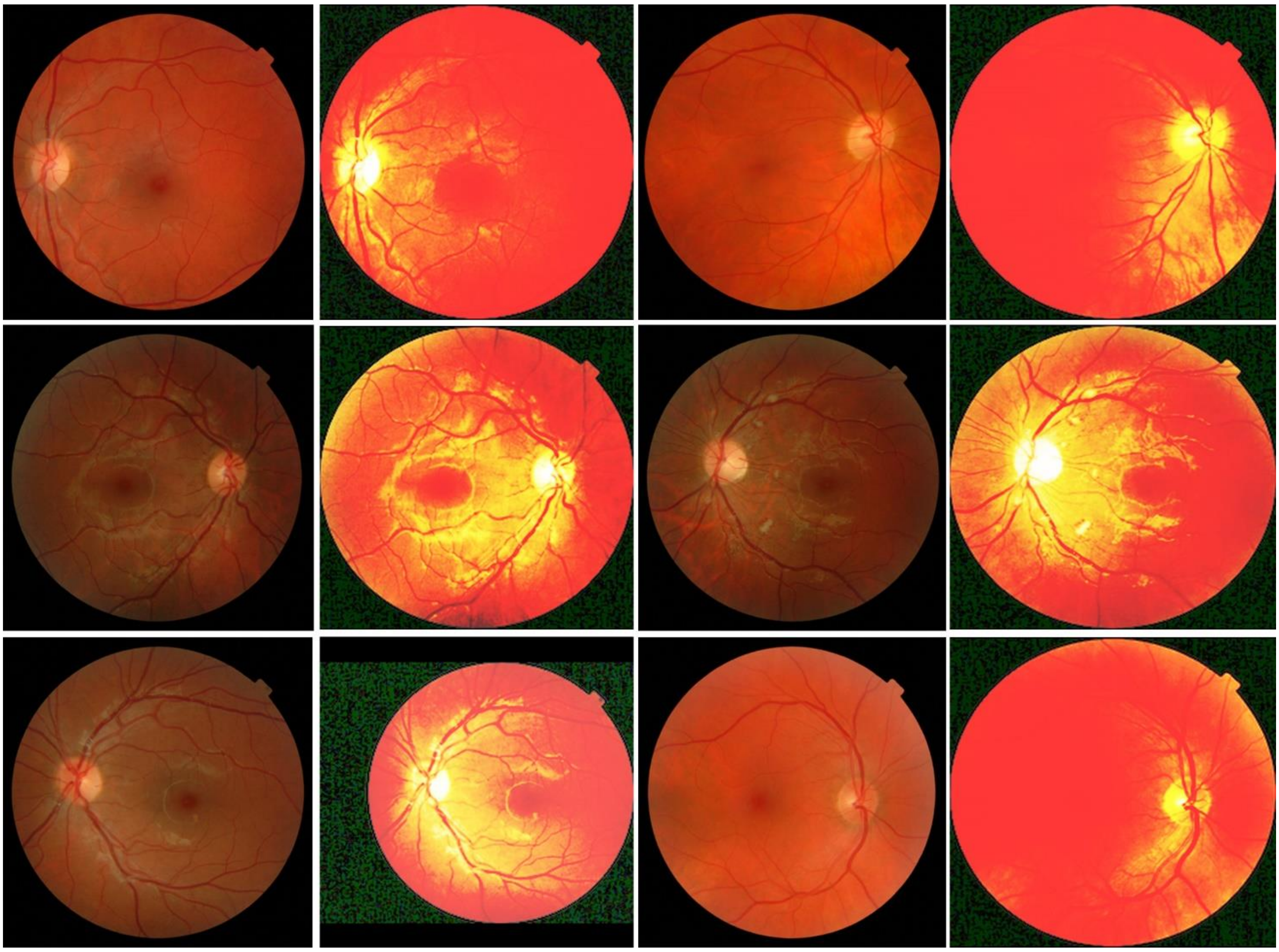


Figure 18: Filtering by Saturation

Channel Extraction:

Color fundus image is converted into green-channel image in order to facilitate the blood vessels segmentation and to decrease the computational time. The green-channel image provides maximum local contrast between the background and fore- ground. In the next step we extract the green-channel image from color fundus image.

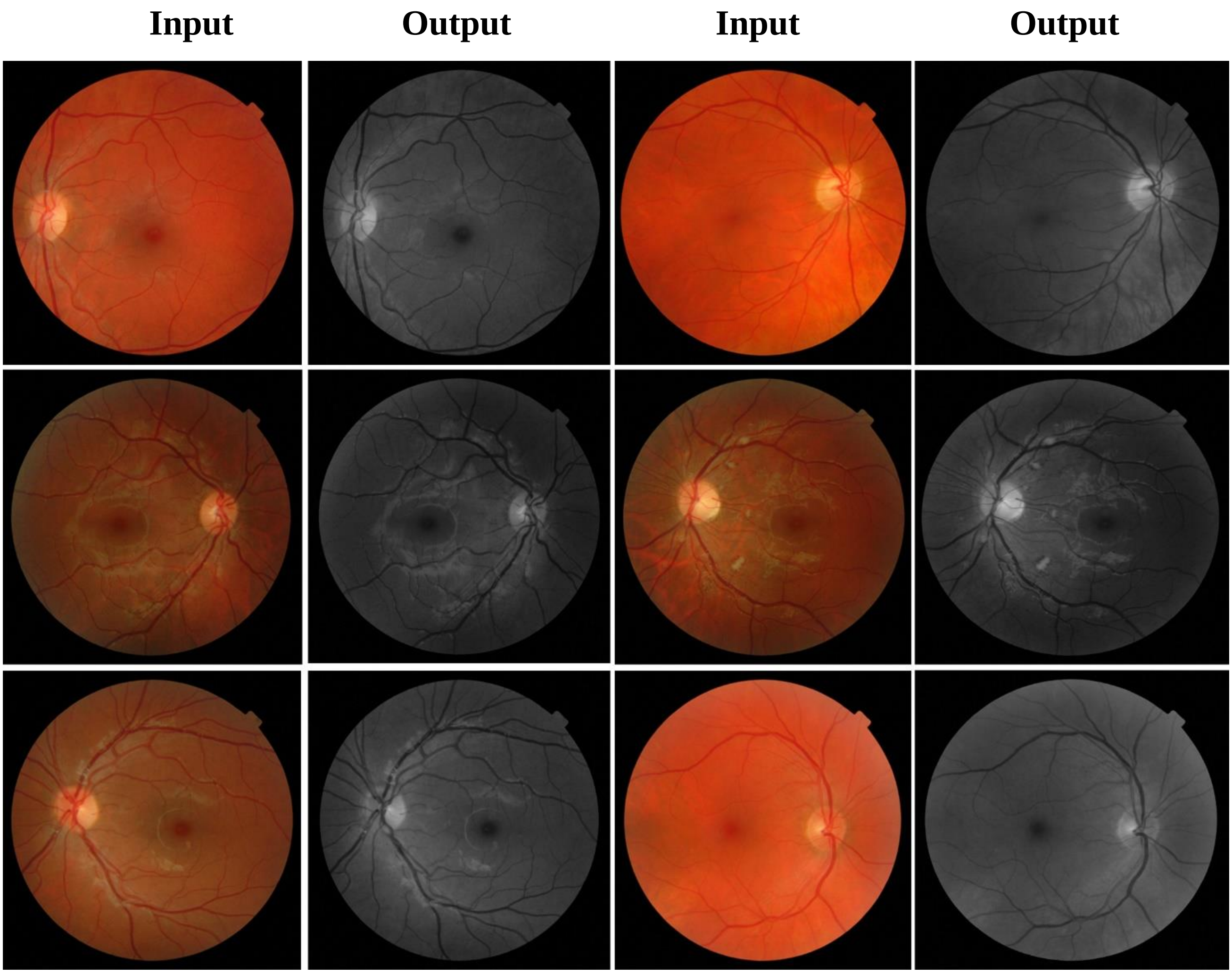


Figure 19: Filtering by Saturation

CLAHE Enhancement:

To reduce the noise effect in color retinal image due to the acquisition process, we need to enhance this image. In this step we further enhance the contrast of green channel extracted images to get better result.

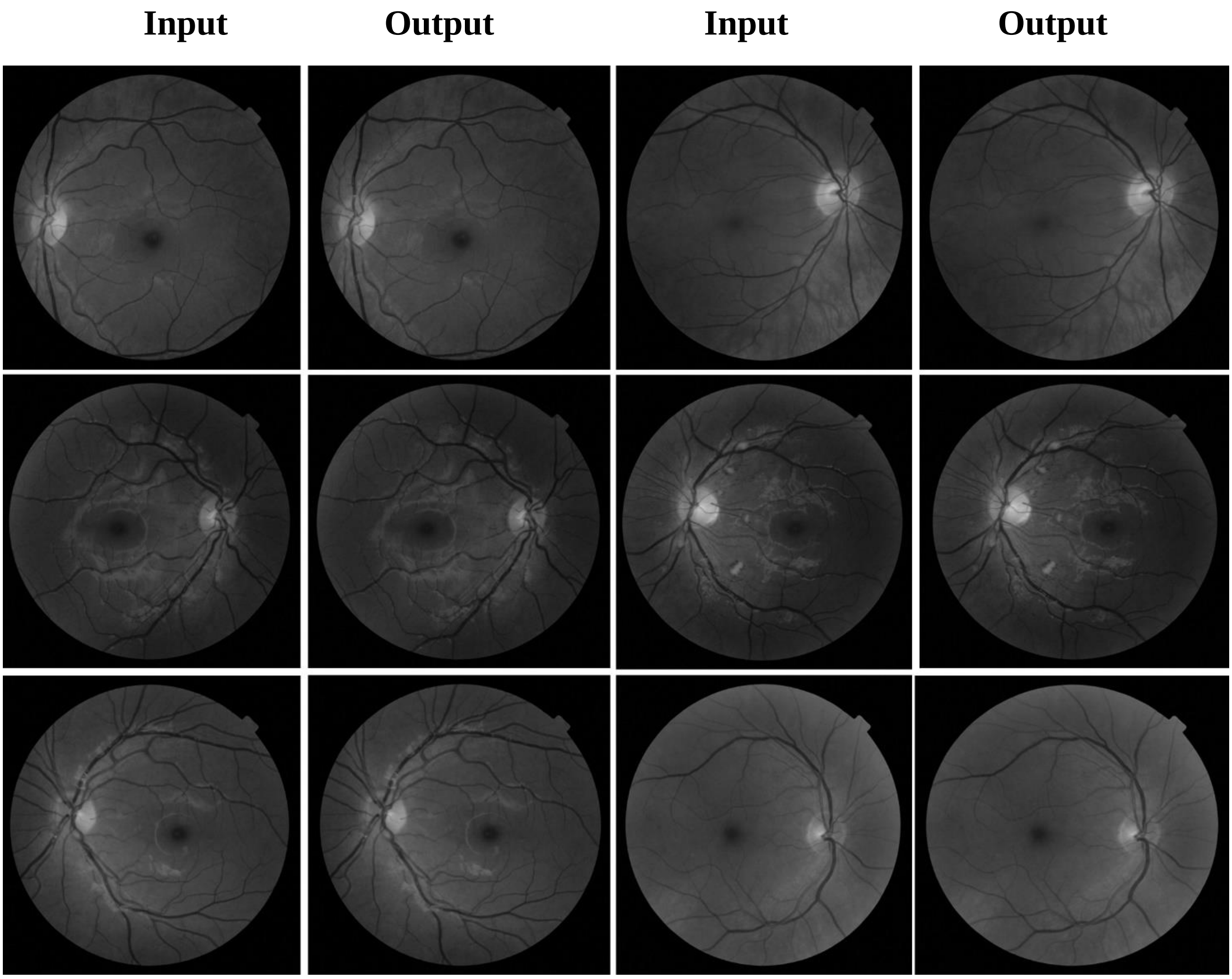


Figure 20: After further enhancement

Morphological Filter Using SE=5:

Morphological filter can be applied through image filtering to grow or shrink image regions, as well as to remove or fill-in image region boundary pixels. Additional morphology filters include top-hat transforms. morphological gradient, and morphological Laplace, Alternative sequential filter. In the following figure we have shown the output of morphological filter.

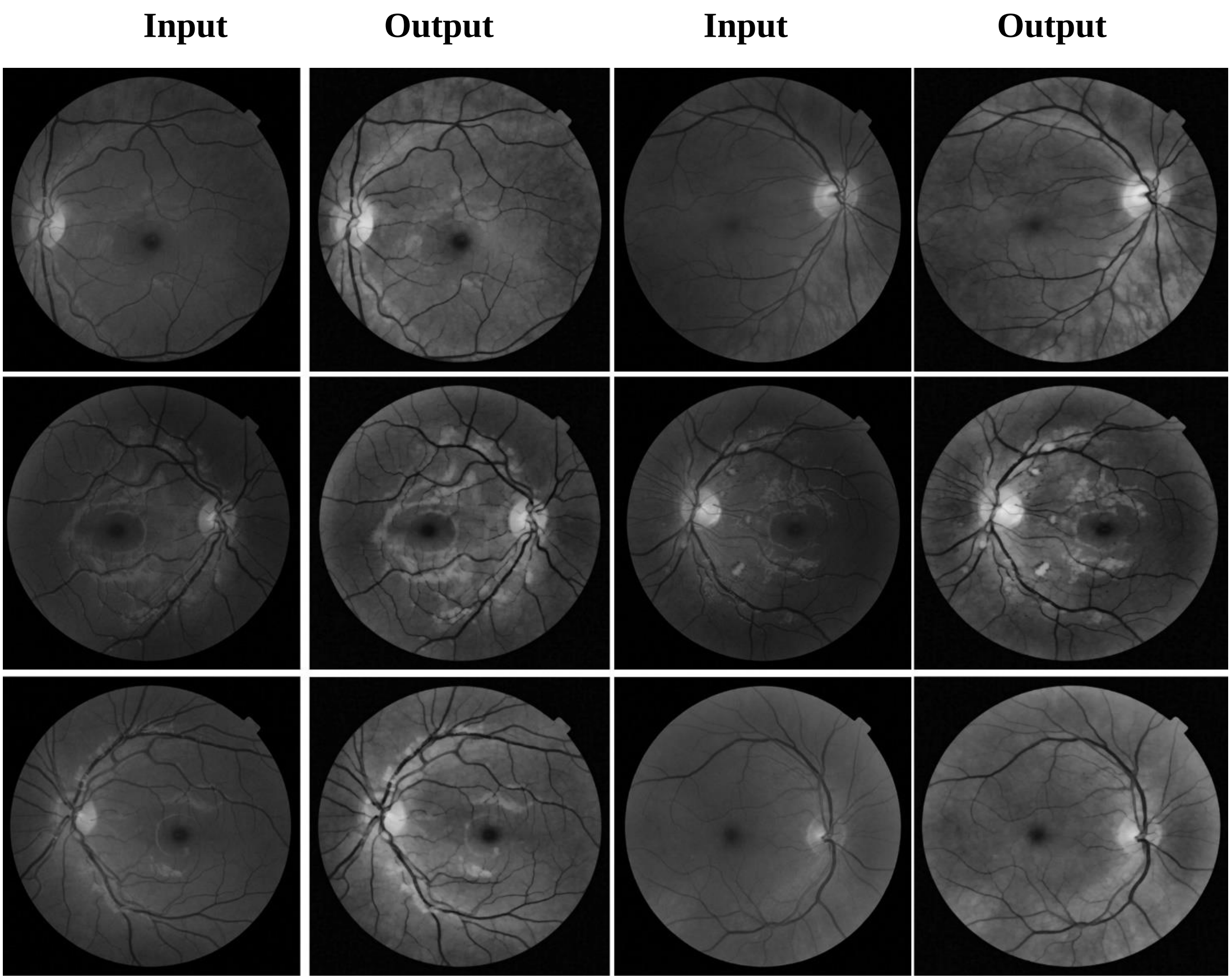


Figure 21: Using morphological filter

Thresholding:

Thresholding is to convert everything to white or black, based on a threshold value. A binary threshold is a simple "either or" threshold, where the pixels are either 255 or 0. In many cases, this would be white or black, but we have left our image colored for now, so it may be colored still. The first parameter here is the image. The next parameter is the threshold, we are choosing 15. In the following figure we have shown the output of filtered image taking thresholding value as 15.

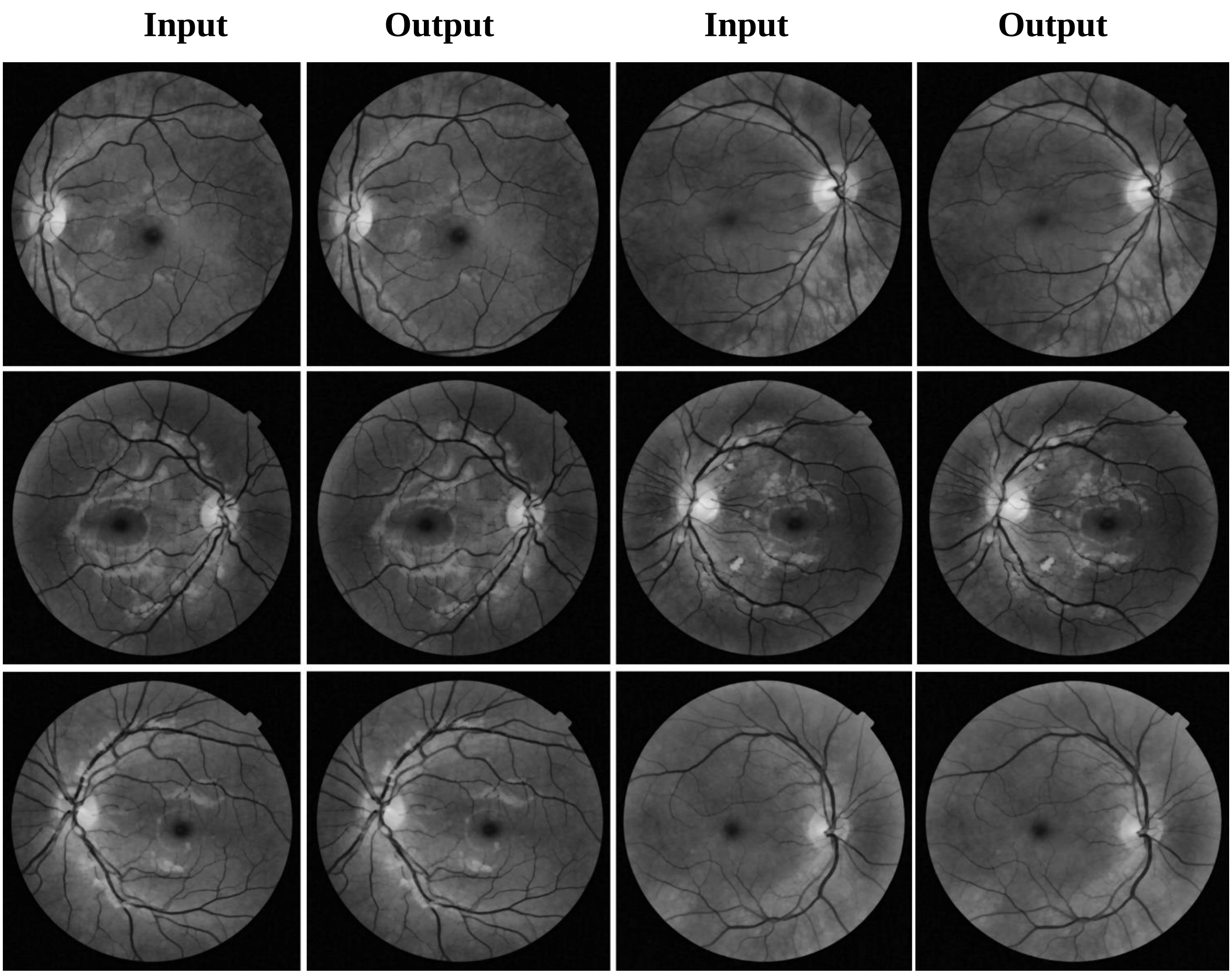


Figure 22: The output after taking thresholding value as 15

Blood vessels extraction:

In this step we finally extracted the Blood vessels from above filtered output. In the following figure the final blood vessels segmentation has been shown.

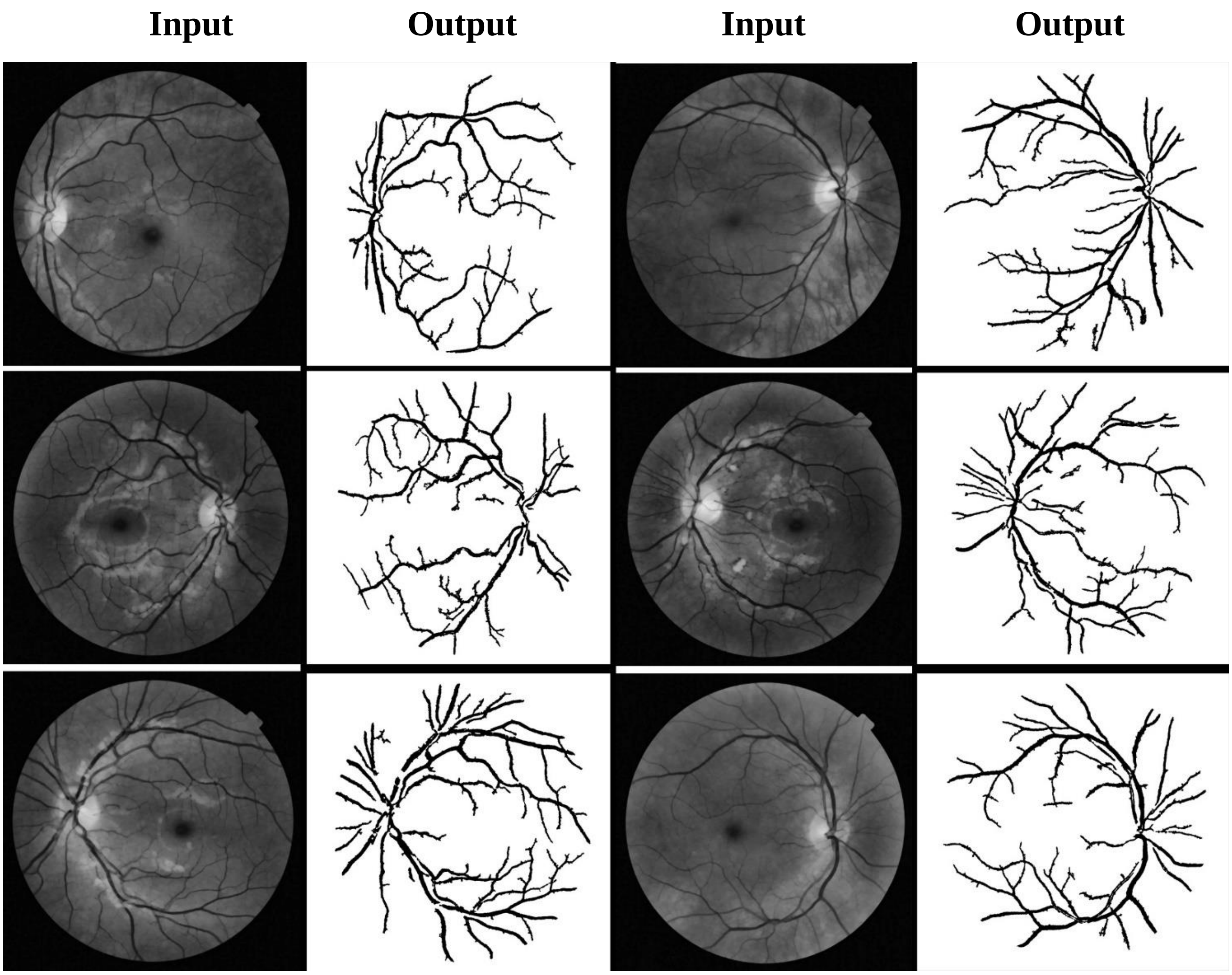


Figure 23: Segmented blood vessel

Morphological Filter Using SE=6:

Morphological filter can be applied through image filtering to grow or shrink image regions, as well as to remove or fill-in image region boundary pixels. Additional morphology filters include top-hat transforms. morphological gradient, and morphological Laplace, Alternative sequential filter.

In this step we again use morphological filter using SE=6. The following figure shows the output.

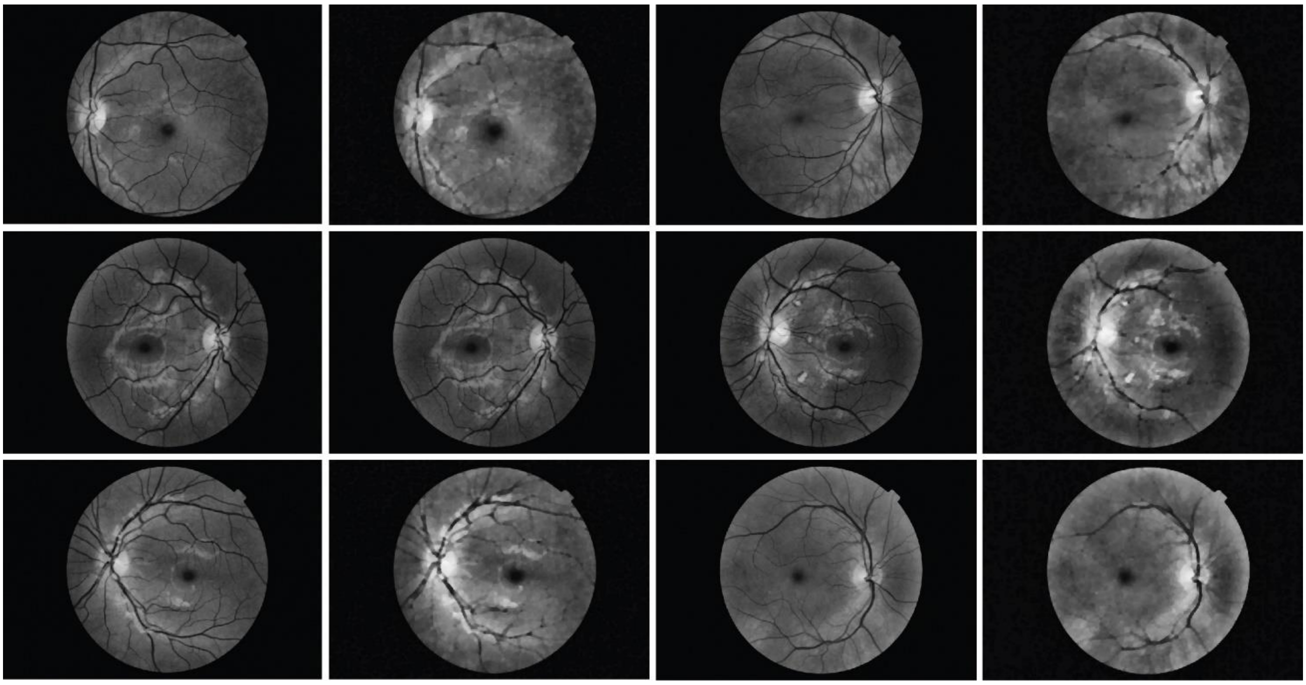


Figure 24: Output of morphological filter

Edge Detection:

Edge detection is an image processing technique for finding the boundaries of objects within images. It works by detecting discontinuities in brightness. In this step we have subtracted the morphological output from edge detection output.

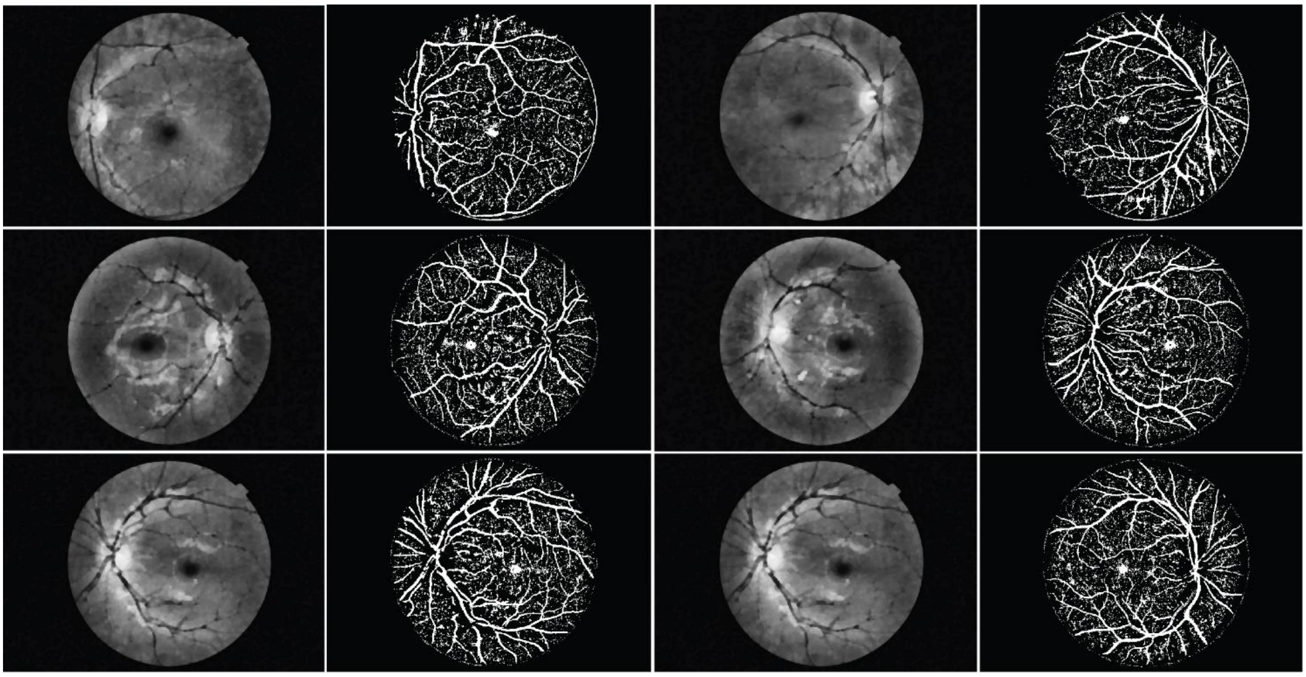


Figure 25: Output after edge detection

Microaneurysms Extraction:

In this step we have subtracted the blood vessels from previous step output to get microaneurysms extracted. The result is shown below.

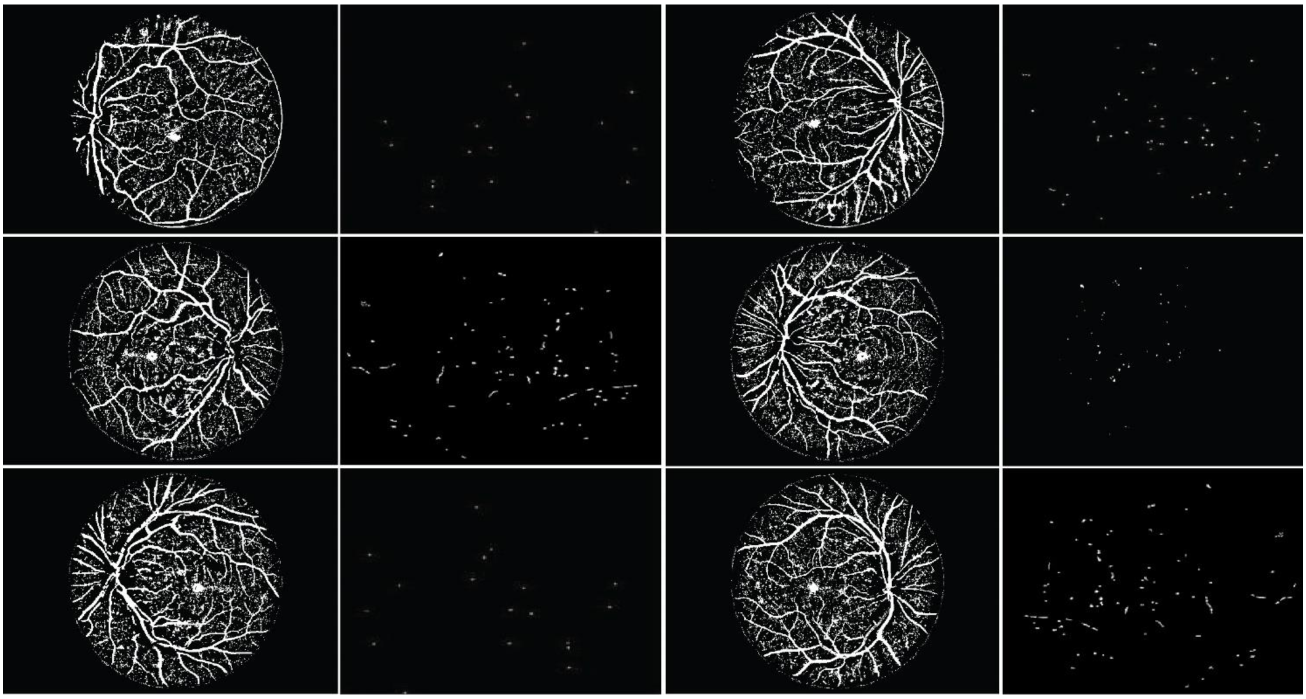


Figure 26: Microaneurysms Extracted

Conclusion

Discussion:

To detect diabetic in early stage the detection of diabetic retinopathy is very important. Diabetic retinopathy can be detected by examining fundus images. Automatic computer programs can detect retinopathy with the help of some features like exudates, Microaneurysms, Blood vessels, etc. In Our work we have designed a program which can automatically extract Microaneurysms (MA) from raw retinal fundus images. The result is absolutely accurate and speed and accuracy is quite satisfactory.

Future Opportunities:

Our work can be continued further more by feeding the outputs only containing Microaneurysms (MA) to any of the reputed classifiers, or any newly developed algorithm of higher accuracy which can show us the percentage of DR patient has or possibility of having DR.

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