DETECTION OF DIABETIC RETINOPATHY USING DIGITAL IMAGE PROCESSING

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By

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DECLARATION

I hereby declare that the work reported in the B.Tech Project Report entitled "**Detection of Diabetic Retinopathy Using Digital Image Processing**" submitted at **Jaypee University of Information Technology, Waknaghat, India** is an authentic record of our work carried out under the supervision of **Prof.** (**Dr.) Shruti Jain**. This work has not been submitted for any other degree or credential to any other University or Institute.

Signature of Student

Vinayak Tiku

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This is to certify that the foregoing statement stated by the candidates is true to the best of my knowledge.

Signature of the supervisor

Prof. (Dr.) Shruti Jain

Date:

Head of the Department/Project Coordinator

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Besides hard work, the success of a project is heavily dependent on the support and guidance of many individuals. I'd want to use this opportunity to express my gratitude to everyone who helped me with this project and made it a success.

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Last but not the least, I'd want to thank **Jaypee University of Information Technology** for providing me with a forum to bring the several disciplines I've explored and learned to life and execute them.

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ABSTRACT

Diabetic Retinopathy, which is marked by gradual degeneration of retinal blood vessels, is thought to be the underlying reason for extreme visual impairment in diabetes. Regular screening and diagnosis can help to alleviate this condition to a large extent. Automatic optical disc segmentation and automated blood vessel withdrawal results in accurate diabetic retinopathy detection, lowering the risk of vision loss. While several studies have made significant progress toward automating ophthalmic image processing via computer assisted screening, retaining picture quality comparable to the original fundus image remains a difficulty.Optical Disc Segmentation approaches based on thresholding, region expanding algorithm, and mathematical morphology were assessed in this article for successful abolition of optical disc to assist blood vessel extraction. For accurate blood vessel extraction, a novel approach based on mathematical morphology and a fuzzy algorithm is presented. For performance evaluation of the suggested technique, two open access standard fundus image datasets, DRIVE and STARE, were used. This method is effective in recognizing the optical disc and extracting blood vessels around it, which is significant in the early detection of diabetic retinopathy.

CHAPTER 1

INTRODUCTION

Diabetic Retinopathy (DR) is defined as long-term cumulative damage to the retina caused by diabetes mellitus, as evidenced by the formation of microaneurysms, exudates, hemorrhages, neovascularization, and other abnormalities. DR is the most common cause of vision loss among diabetics, and it is caused by a change in the retinal blood vessels, which can expand and leak fluid into the retinal region.[1] These blood arteries may totally shut, cutting off oxygen to the retina. Blood vessel overgrowth, which results in a bifurcated blood vessel pattern, is another primary cause of DR. Because the newly formed blood vessels are thin and delicate, blood and fluid may seep into the retinal regions. There are main two different types of Diabetic Retinopathy i.e. Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). The optical disc and blood vessels are the two basic features employed in fundus image analysis. The brightest section is the optical disc (OD), which shows in fundus photography as a brilliant yellowish circular or oval-shaped zone. Blood vessels are crucial for delivering sustenance to the eye and begin from the centre of the optical disc [3]. The bifurcation and elimination of OD is an important step in image processing for automated identification of DR lesions, as incorrect removal of OD might cause misclassification of bright lesions like EXs.Because blood vessels show in fundus photography as black elongated structures, inaccurate identification of blood vessels may obstruct the detection of dark lesions like MAs and HEMs.

1.1 OBJECTIVE-

Medical imaging technology is transforming medicine due to its fast growth and dissemination. By peeking noninvasively into the human body, medical imaging provides researchers and clinicians with plausibly life-saving insights.as medical imaging plays an extremely essential role in illness diagnosis and therapy, the medical image analysis community grown fascinated with the tough task of obtaining clinically useful information from anatomic structures imaged by Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), and other modalities using computers.
Picture segmentation, which tries to automate the extraction of object boundary characteristics, is critical for comprehending image content in medical image archives for searching and mining. For big scalar longitudinal projects, manual segmentation is typically impracticable. To overcome the constraints of manual segmentation, strong picture segmentation algorithms must be developed.

The use of computers to aid in the processing and interpretation of medical pictures has become important as their size and number have grown. Computer methods for delineating anatomical structures and other locations of importance, in particular, are a critical component in helping and automating specialised radiological operations. Image segmentation algorithms are used in a variety of biomedical imaging techniques, including diagnosis, disease location finding, anatomical structure study, tissue volume estimation, partial volume rectification of operational imaging data, treatment planning, and computer-aided operations.

The requirement to segment retinal pictures drove the automated approaches and procedures presented in this paper. The use of these methods, on the other hand, is appropriate for more general segmentation issues using any imaging modalities or segmentation goals. Segmenting the retinal blood vessels by hand is difficult and time-consuming. As a result, automatic segmentation is beneficial since it saves time and effort. Most algorithms for retinal blood vessel segmentation focus on automated detection of diabetic retinopathy, which has recently been identified as the leading cause of blindness in a single image, but intensity information alone is frequently insufficient for an algorithm to distinguish target structure from high folded and interconnected neighbours.

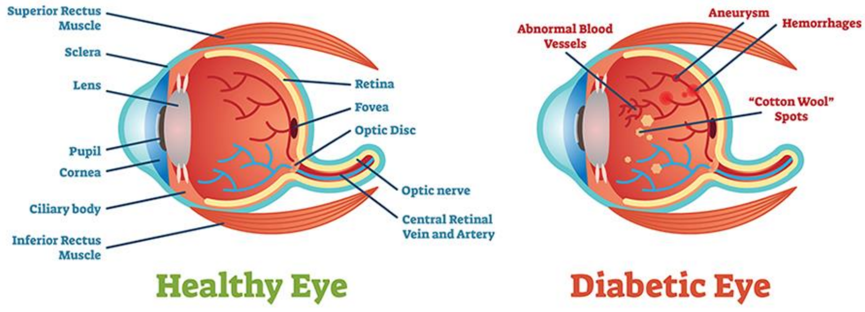


Figure 1: Healthy & Diabetic eye [4]

1.2 INTRODUCTION TO THE PROJECT-

The main goal of this course is to introduce students to basic ideas and techniques in medical image processing and to pique their interest in future research and study in this field. Developing computer tools and algorithms to interpret and quantify biological data is also a priority. Image processing and analysis algorithms are being developed and improved in response to the growing volume of photos and the aim to eliminate human subjectivity. Segmenting the retinal blood vessels by hand is difficult and time-consuming. As a result, automatic segmentation is beneficial since it saves time and effort. Image quality, which is impacted by variables such as medial opacities, defocus, or the presence of artefact, is one of the challenges in image capture of the ocular fundus.The initial clinical symptom of Diabetic Retinopathy is micro aneurysms (MAs). Early identification of MA can assist to prevent blindness. The goal of our project is to detect diabetic retinopathy in its early stages utilising non-dilated retinal pictures. Our proposal provides an automated technique for detecting diabetes afflicted eyes among multiple retinal pictures supplied. Pre-processing, segmentation, and disease abnormalities detection are the three processes involved. Performance measures are used to assess the proposed technique.

CHAPTER- 2

RETINAL IMAGE PROCCESSING

2.1 PROPOSED METHOD

The human eye is a light-sensitive organ which allows us to view what is happening around us. The picture is generated on the retina of the eye, similar to a camera, but a regular camera generates the image on film. The human eye's cornea and crystalline lens are similar to camera lenses, and the iris functions similarly to a camera's diaphragm, which adjusts the size of the pupil to control the quantity of light reaching the retina. The retina, which includes the light-sensitive photoreceptors, receives light that passes via the cornea, pupil, and lens. The picture created on the retina is converted into electrical impulses and sent to the brain via the optic nerves, where the signals are processed and the feeling of vision is produced.

The macula is a tiny, yellowish centre region of the retina that is roughly 5.5 mm in diameter. Sharp central vision is provided by the macula and its centre region (fovea). A healthy macula can produce vision that is at least 20/20. The fovea is heavily packed with 'cone' photoreceptors, that are essential for the trichromatic aspect of human colour vision. There are no 'rod' photoreceptors in the fovea, that provide luminance data. Long, middle, and short wavelength ranges in the visible part of the electromagnetic spectrum (i.e., 380-780 nm) are sensitive to L, M, and S-cone cells, respectively, but rod cells offer no colour information.

The visible region of the optic nerve where the optic nerve fibres and blood vessels enter the eye is called the optic disc. Because it lacks rod and cone photoreceptors, it is unable to respond to light. As a result, it's also known as a blind area. The optic disc is where the retinal arteries and veins arise. The retina is a multi-layered membrane that connects the interior of the eye and turns entering light rays into a neuromodulator that the brain's visual cortex can evaluate subsequently. As a consequence, it functions as a brain extender. It's pretty fascinating to be able to film the retina and construct tools for assessing the images. The ocular structures tangled in image production has to be optically clear since the retina's function needs it to perceive the outside environment.As a result, the retina may be seen from the outside, making retinal tissue, and hence brain tissue, non-invasively accessible for imaging. The retina permits direct non-invasive observation of the circulation since its role makes it a highly metabolically active tissue with a twofold blood supply.

In the industrialized nations, ocular diseases like glaucoma and macular degeneration are the primary and third sources of eyesight loss. A variety of systemic disorders can potentially impact the retina. Diabetic retinopathy, the second leading reason of blindness in the civilized countries, hypertensive retinopathy caused by coronary heart disease, and multiple sclerosis are all consequences of systemic diseases. Furthermore, the retina is susceptible to organ-specified and systemic disorders, yet imaging the retina enables for the identification, evaluation, and control of eye diseases as well as the effects of hypertension, diabetes, and other cardiovascular problems.

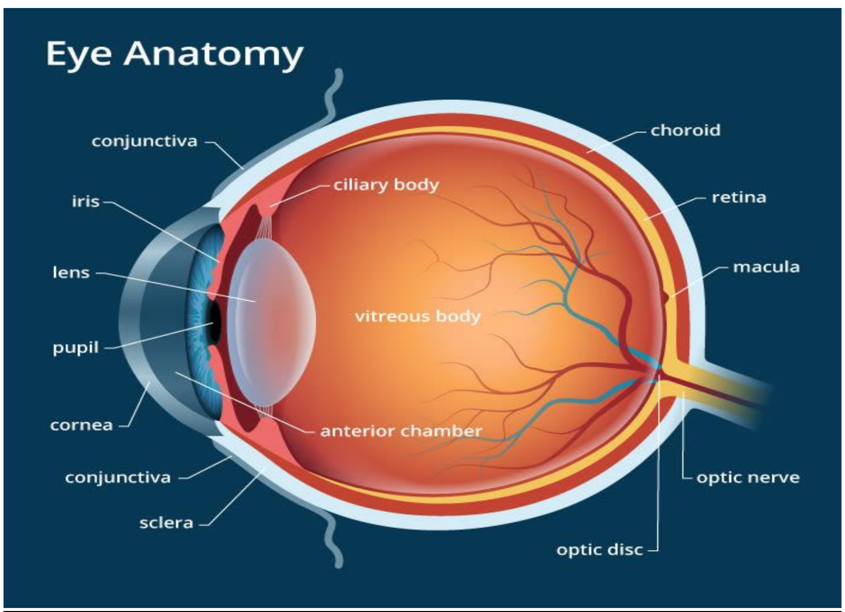


Figure 2: Eye anatomy

2.2 RETINAL MANIFESTATIONS OF EYE AND SYSTEMIC DISEASE

Many serious disorders present in the retina and have their origins in the eye, brain, or cardiovascular system. Following is a quick rundown of the most common disorders that may be researched using eye imaging and image processing.

2.2.1 Diabetes According to the World Health Organization's current definition, diabetes mellitus is diagnosed when a patient's fasting plasma glucose level exceeds 7.0 mm/l. Although the causes are unknown, genetics, obesity, and a sedentary lifestyle all increase the risk of developing diabetes. Dietary adjustments, insulin injection, and/or anti-hyperglycemic medicines are the mainstays of treatment. Hyperglycemia, or high blood sugar, affects tiny and big blood vessels as well as nerve cells, causing damage to the kidneys, heart, brain, and eyes, resulting in diabetic retinopathy, a retinal consequence of diabetes.

2.2.2 Diabetic retinopathy (DR) is a consequence of diabetes mellitus that is the world's second leading cause of blindness and vision loss, and the leading cause among people in their working years. The number of diabetic patients is steadily rising, reaching 23.5 million in 2007. There is ample evidence that yearly screening and early diagnosis can avoid blindness and vision loss in these people. Hyperglycemia affects the retinal vessel walls of the eye, resulting in: 1 prefix-word= mark-type=decimal list-behavior=enumerated 2 Ischemia, which causes the formation of new blood vessels that might haemorrhage and/or induce retinal detachment, a disease known as proliferative diabetic retinopathy; 3 The blood-retinal barrier breaks compromised, causing fluid leakage, diabetic macular edoema (DME), anddamage to photoreceptors. DME, which is more frequent in Type-2 diabetes, is the leading cause of vision loss in diabetics. The blood-retinal barrier breaks down, allowing dilated hyperpermeable capillaries and micro aneurysms to seep into intracellular and extracellular retinal tissue, resulting in fluid buildup.

DME clearly has an impact on macular structure in the short and long term. The leaky exudate in DME penetrates the cytoplasm of Müller's cells (radial glial cells of the retina), predominantly in the outer retina, however fluid buildup has been reported in more advanced stages of DME to spread through most macular layers. Cysts (extracellular fluid in the retina) are most common in the outer retina. Cysts in the outer retina tend to merge and expand into the inner retina over time. The remaining retinal tissue atrophy or apoptosis happens in these circumstances. Serous detachment occurs in around 20% of DME patients and does not appear to be linked to visual acuity.Exudates that are hard in nature tend to develop at the level of the outer plexiform layer. Patients with long-term DME who have poor vision have lower photoreceptor directional sensitivity and lower visual pigment density.

Diabetes is largely managed by reducing blood sugar levels by food, lifestyle modifications, and anti-diabetic medicines. If DR is present, major randomised clinical studies have indicated that treating CSME and proliferative DR with laser photocoagulation, anti-vascular growth agents, and steroids can avoid blindness and subsequent vision loss.

2.2.3 Age-Related Macular Degeneration The most prevalent cause of vision loss is age-related macular degeneration (AMD), which is an increasing public health concern. Wet AMD, also known as Choroidal Neo Vascularization (CNV), is the most visually dangerous kind of AMD. It is marked by the ingrowth of a Choroidal vascular structure into the macula, as well as increased vascular permeability. When vascular permeability increases, aberrant fluid collects inside or under the retina, causing visual impairment when it affects the macula's centre. CNV is characterised by rapidly declining visual acuity, scarring of the pigment epithelium, and irreversible vision loss or blindness. Many people can halt the progression of dry AMD with dietary supplements, whereas wet AMD is treated with anti-vascular growth factor administered intravitreally.

2.2.4 Glaucoma Glaucoma is the third most common cause of blindness, characterised by progressive damage to the optic nerve and consequent vision loss. Early detection and treatment have been found to reduce the risk of glaucoma-related vision loss. Glaucoma is a neuropathy, not a retinopathy that damages ganglion cells and their axons in the retina. Glaucoma is defined by the cupping of the optic disc, which is the visual expression of the ONH's 3-D structure. Two-dimensional images of the optic disc can be obtained using indirect stereo bio microscopy or stereo colour fundus photography. The cup-to-disc ratio, or the ratio of the optic disc cup and neural retinal rim surface areas in these pictures, is a significant structural diagnostic for glaucoma detection and development.

2.3 IMAGE PROCESSING

Modern digital technology allows systems ranging from simple digital circuits to powerful parallel computers to manage multi-dimensional signals. In the "real world," an image is described as a function of two real variables, such as a(x,y) with an as the picture's amplitude (e.g. brightness) at the real coordinate point (x,y). Sub-images, also known as regions–of–interest, ROIs, or simply regions, can be found in a single picture. This idea stems from the fact that photographs usually contain groups of items, each of which might serve as the foundation for an area. It should be feasible to apply certain image processing procedures to specified locations in a sophisticated image processing system. As a result, one section of an image (region) may be treated to reduce motion blur while another is handled to improve colour rendering.

A given image's amplitudes will nearly always be either real or integer values. The latter is generally the outcome of a quantization procedure that reduces a continuous range (say, 0 to 100 percent) to a discrete number of levels. However, in some image-forming processes, the signal may include photon counting, which indicates that the amplitude will be quantized intrinsically. The direct physical measurement gives a complex number in the form of a real magnitude and a real phase in other image-forming processes, such as magnetic resonance imaging.

Digital Image

Through a sampling process known as digitization, a digital picture a [m, n] represented in a 2D discrete space is created from an analogue image a(x,y) in a 2D continuous space. I'm looking forward to some fundamental definitions for digital images. A (x, y) is segmented into N rows and M columns in a 2D continuous picture. A pixel is the intersection of two rows and columns. a[m,n] is the value allocated to the integer coordinates [m,n], where m=0,1,2,...,M–1 and n=0,1,2,...,N–1. In most situations, a(x,y) – which we can think of as the physical signal that impinges on the face of a 2D sensor – is really a function of a number of factors, including depth (z), color (λ), and time (t). The process of representing the amplitude of the 2D signal at a given coordinate as an integer value with L different gray levels is usually referred to as amplitude quantization or simply quantization.

2.4 APPLICATIONS OF IMAGE PROCESSING

Image processing applications - The most important type of data which the human brain detects, analyses, and analyzes is visual information. A third of the cortical region of the human brain is dedicated to visual information processing. Digital image processing is a computer-centered innovation that automates the computation, manipulation, and explanation of visual information. It is used in a broad array of disciplines and areas in science and technology, including photography, robotics, television, remote sensing, industrial assessment, and medical diagnosis.

• Computerized photography (e.g., Photoshop)
• Remote sensing: analysis of aerial and satellite images
• Recognition of characters automatically (zip code, license plate recognition)
• Recognition of fingerprints, faces, and irises
•Industrial applications (e.g., product inspection)
• Reconnaissance

2.5 BLOCK DIAGRAM OF IMAGE PROCESSING

The picture taken by the camera is digitised during image acquisition. The practise of modifying a picture such that the results are more appropriate for various uses is known as image enhancement. The look of a picture is improved via image restoration, which tends to probability. picture degradation model Morphological processes are methods for extracting picture components for use in image description and display. The most challenging task in digital image processing is picture segmentation, which isolates objects from the background. The choice of whether to portray data as a border or as a whole region is made by representation. The process of assigning a label to an item based on information supplied by its descriptor is known as recognition as shown in figure 3.

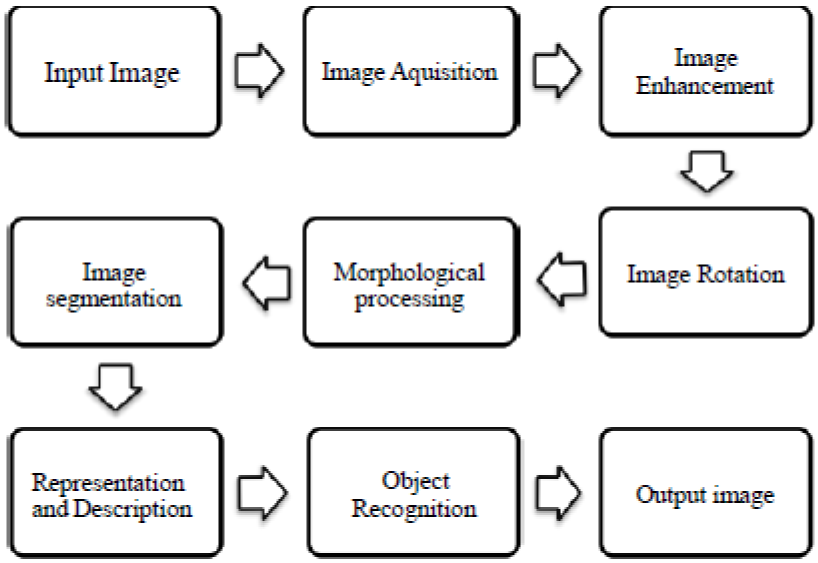


Figure 3: Block Diagram of Image Processing

CHAPTER 3

PROPOSED METHODOLOGY

3.1 INTRODUCTION

The proposed method is a fast and robust one to extract exudates in color eye fundus image which is based on mathematical morphology where Blood vessels extraction is carried out which is followed by extraction of the hard exudates and optic disc and finally detection of the optic disc which is used for distinguishing it from exudates. The proposed methodology is given in figure 4.

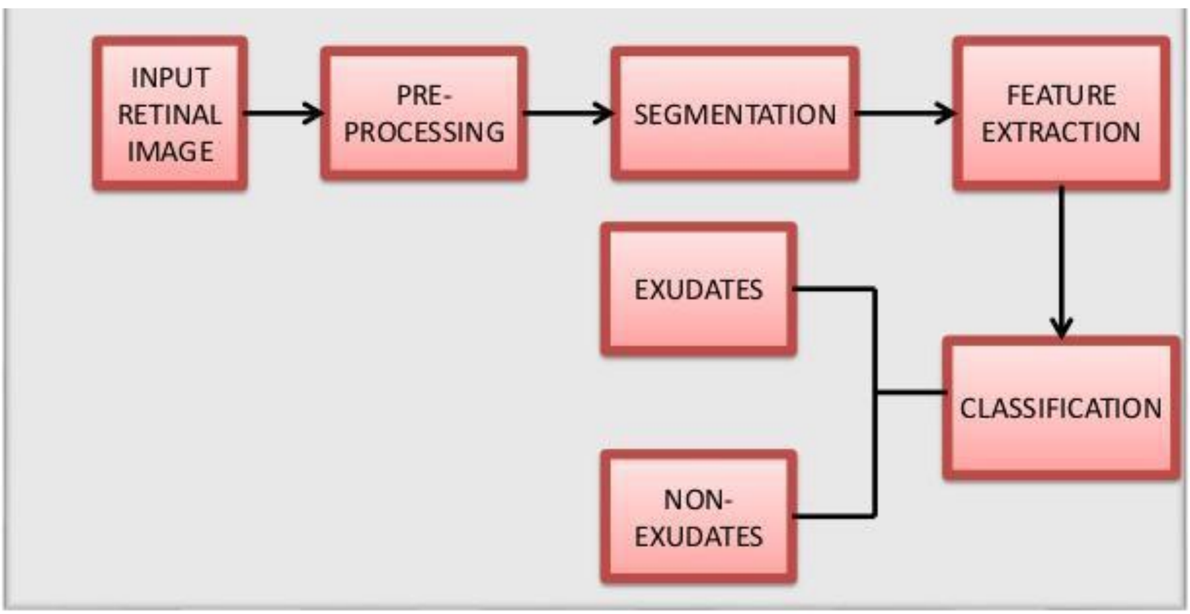


Figure 4: Block Diagram of Proposed Methodology

3.2 PRE-PROCESSING OF RETINAL IMAGES

The photos must be Pre-Processed in order to correct difficulties such as uneven illumination, insufficient contrast between exudates and image backdrop pixels, and the presence of noise in the input fundus image for detecting anomalies connected with fundus images. Pre-processing is an important step in retinal image analysis that reduces picture fluctuation by comparing the original image to a prototype.

Low Pass Filters

To smooth a picture, a low-pass filter is utilised. By cancelling out quick fluctuations from pixel to pixel, this lessens the impact of noise. Noise shows in the picture as random areas with considerably differing values than their nearby pixels. The brightness of light from the object being captured seldom varies that quickly; rather, it fluctuates gradually over several pixels.

Histogram Equalization:

Histogram equalisation is a technique for enhancing contrast by altering picture intensities. To equalise the histogram of the produced image and make it a constant by transforming the grey levels of the image:

$$h[i] = \text{constant}, \qquad 0 \leq i < L$$

The purposes:

• To equally use all available gray levels

• For further histogram specification.

3.3 BLOOD VESSLE EXTRACTION

As part of the automated diagnosis of the disease process, blood vessels can be extracted and measured to estimate the degree of disease.

Step 1: Read Input color image.

Step 2: Convert it into Gray image.

Step 3: Apply the threshold.

Step 4: By using kirsch's templates blood vessels are extracted. The color eye image obtained from the fundus camera is converted into gray image and applies the threshold required. Now, by using the Kirsch templates blood vessels are extracted.

3.3.1 Kirsch Operator

The Kirsch compass kernel, sometimes known as the Kirsch operator, is a non-linear edge detector that detects the highest edge strength in a few preset directions. Russell A. Kirsch, a computer scientist, was the inspiration for the name. The operator spins a single kernel mask across all eight compass directions in 45 degree increments: N, NW, W, SW, S, SE, E, and NE.

3.3.2 Prewitt Operator

The Prewitt operator is extensively used in edge detection approaches in image processing. It's a distinct differentiating operator which calculates a rough estimate of the gradient of the image intensity value. At each point in the image, the Prewitt operator gives either the appropriate gradient vector or the standard of this vector. The Prewitt operator uses a small, discrete, integer-valued filter to convolve the image in vertical and horizontal dimensions, and so is less expensive than the Sobel operator in terms of calculations. On the other side, the gradient estimate it produces is rather harsh, mainly for high-frequency changes inside the image. In simple terms, the operators define the image intensity gradient at every point, representing the maximum potential climb from light to dark and the rate of variation in that order. As an outcome, the result shows how "quickly" or "seamlessly" the image alters at that moment, suggesting how probable that portion of the image indicates an edge and also how probable that edge is oriented.

3.3.3 Sobel Operator

The Sobel operator also referred to as the Sobel–Feldman operator or Sobel filter is a technique used to highlight edges in pictures in computer vision and image processing. It's a discontinuous differentiating operator which calculates a rough estimate of the gradient of the image intensity function. At each point in the image, the Sobel–Feldman operation yields either the appropriate gradient vector or its standard. The Sobel–Feldman operator is computationally cheap because it uses a modest, discrete, arithmetic filter.

‘to convolve the image in the horizontal and vertical axes. On another extreme, the gradient approximation it gives is rather imprecise, mainly for high-frequency variations in the image. The operator uses two 33 kernels intertwined with the original image to obtain approximations of the derivatives: one for horizontal alterations and another for vertical variations. Since the Sobel kernels might well be deconstructed as the products of an average and a differentiating kernel, the gradient is calculated with smoothness.

3.3.4 Canny Operator

The Canny edge detector is a multi-stage edge detection operator that identifies a wide variety of edges in photographs. Canny edge detection is a method for obtaining structural input from a range of graphic elements while drastically lowering the amount of data to be analyzed. It has been implemented in a number of computer vision applications. Canny showed that the requirements for employing edge detection on different vision systems are quite similar. As a consequence, an edge detection method that fits these criteria can be applied to a wide range of circumstances. Detection of edges with low error rate, which indicates that the detection should accurately catch as many edges presented in the picture as feasible, is one of the general requirements for edge detection. The edge point recognized by the operator should be accurate in locating the edge's centre. A particular picture edge should only be tagged once, and image noise should be avoided if feasible.

One of the common requirements for edge detection is the identification of edges with a low error rate, which means that the detection should properly catch as many edges shown in the picture as possible. The operator's recognition of an edge point should be correct in determining the edge's centre. If at all possible, just one image edge should be identified, and image noise should be avoided.

The Canny edge detection technique may be separated into five distinct steps:

1. Refine the image with a Gaussian filter to eliminate the clutter.
2. Locate the image's luminance gradients.
3. Use non-maximum reduction to eliminate erroneous edge detection responses.
4. Identify probable edges using a twofold threshold.
5. Use hysteresis to detect edges. Disable any edges which are feeble and not related to strong edges to complete the edge detection process.

3.3.5 Robert Operator

Discrete differentiation, which involves combining the squares of variations among diagonally neighboring pixels, was used to make the image. An edge detector, according to Roberts, ought to have specific traits: the produced edges must be well-defined, the background should provide as little interference as practicable, and the edge severity must be as close to how a person might experience as feasible.This operation's output will show variations in intensity in a diagonal direction. The simplicity of this procedure is one of its most appealing features; the kernel is minimal and just comprises numbers.

3.3.6 Hard Exudates Extraction

Automated early identification of exudates can help ophthalmologists more effectively prevent the illness from spreading. As a result, detecting exudates is a critical diagnostic job.

Step 1: Read Input color image
Step 2: Green component of input image is extracted.
Step 3: Morphological Bottom hat operation is performed on the green component of the image.
Step 4: Morphological Top hat operation is performed on the green component of the image.
Step 5: Subtract resultant image from step 4 with step 3.
Step 6: Optic disc elimination and hard exudates detection.

3.3.7 Optic Disc Detection

The identification of the optic disc is an essential anatomical characteristic in retinal pictures, and it is critical for retinal image processing.
Step 1: Read Input color image.
Step 2: Extract Green channel from input image.
Step 3: Apply Otsu method to obtain fundus region.
Step 4: Perform morphological closing operation to the obtained image.
Step 5: Morphological opening is carried out to the above image.
Step 6: Subtract the above image from green channel image.
Step 7: Top hat and threshold the image obtained from above step.

The picture's green channel is retrieved from the input image. The green channel picture is transformed to a binary image using Otsu thresholding. The binary image is now subjected to morphological closure and subsequently opening operations. As a result, fundus region is generated by subtracting this picture from the green channel image.

3.4 SEGMENTATION OF RETINAL IMAGES

Segmentation's basic goal is to divide an image into sections with similar properties or attributes. It aids in the description of anatomical features and other areas of interest, which is important in image analysis systems.

• Any attempt to analyse or interpret a picture automatically usually starts with segmentation.
• Segmentation is a technique for bridging the gap between low-level and high-level image processing.
• Any application requiring the detection, identification, and measurement of objects in pictures will use some form of segmentation approach.
• The importance of segmentation in most image processing jobs cannot be overstated. The task's success or failure is frequently a direct result of segmentation's success or failure.
• However, using solely automated techniques, trustworthy and precise picture segmentation is extremely difficult to produce.

In the discipline of computer vision, comprehending images and extracting information from them may be utilised for various tasks like as robot navigation, discovering damaged tissues from body scans, detecting malignant cells, and identifying an airport from remote sensing data. Image segmentation meets the aforementioned characteristics. There is a great demand for a method that can be utilised to comprehend photos and extract information or objects. As a result, the initial stage in image analysis is picture segmentation. To avoid erroneous contour selection for segmentation to segment the picture without loss of information for medical diagnostic purposes, noise reduction from the image is sometimes done before the segmentation.

Segmentation is the process of dividing images into component subregions with similar characteristics such as grey level, colour, texture, brightness, and contrast. The subdivision level used is determined by the problem being solved. That is, when the application's objects or regions of interest have been recognised, segmentation should come to an end. The precision of segmentation determines whether automated analytic procedures succeed or fail. Image in photographs, segmentation is commonly used to detect objects and boundaries (lines, curves, etc.). Manual segmentation is feasible, but it takes time and is vulnerable to operator error. Manual segmentation results are difficult to reproduce, and the degree of confidence assigned diminishes as a result.

As a result, automated approaches are preferred. Picture segmentation is the most important and important procedure for delineating, describing, and visualizing regions of interest in any medical image.

The following categories are used:

Threshold Based Segmentation:
The picture is segmented using histogram thresholding and slicing algorithms. They can be used on their own or in combination with other pre- and post-processing procedures.

Edge Based Segmentation:
Detected edges in a picture are supposed to represent object boundaries, and this approach is used to identify these items.

Clustering Techniques:
Although clustering is commonly used interchangeably with (agglomerative) segmentation techniques, we use it here to refer to exploratory data analysis of high-dimensional measurement patterns. Clustering algorithms seek to group together patterns that are related in some way in this setting. This aim is extremely similar to what we're trying to do when we segment an image, and certain clustering approaches may be applied to picture segmentation with ease.

Matching:

When we know what an object in an image looks like (roughly), we may utilise that information to locate the object in the picture. Matching is the term for this method of segmentation.

THRESHOLDING

Segmentation is the process of dividing a picture into sections (or contours) that correspond to objects. We normally try to segment areas by looking for shared characteristics. Alternatively, we can identify contours by looking for differences between regions (edges). Intensity is the most basic feature that pixels in an area might share. So, a logical technique to segment such zones is by thresholding. Threshold is one of the most extensively used picture segmentation algorithms. It aids in the separation of the foreground and backdrop. By selecting an acceptable threshold value T, the grey level image may be transformed to a binary image. All required information regarding the position and shape of the items of interest should be included in the binary picture. The advantage of obtaining a binary image first is that it reduces data complexity and makes the identification and classification process easier.

Selecting a single threshold value is the most popular approach to convert a gray-level image to a binary image (T). The grey level values below T will be categorised as black (0), while those above T will be classified as white (1). The challenge of segmentation becomes one of determining the appropriate value for the threshold T. Analyzing the histograms of the types of pictures to be segmented is a common way for selecting T. The ideal situation is when the histogram only has two dominating modes and a distinct valley (bimodal). The value of T is chosen as the valley point between the two modes in this example.Histograms in real-world applications are more complicated, with several peaks and no obvious valley, therefore selecting the value of T is not always straightforward.

Adaptive Thresholding

When a different threshold is applied for various sections of the picture, it's termed adaptive thresholding. This is also known as dynamic or local thresholding.

Histograms

The histogram is made by dividing the data range into equal-sized bins (called classes). The number of points from the data set that fall into each bin is then tallied for each bin.

Assume that the gray-level histogram corresponds to a picture, f(x,y), consisting of dark objects against a bright backdrop, with grey levels sorted into two dominating modes for object and background pixels. Selecting a threshold 'T' that divides these modes is one apparent technique to isolate the items from the backdrop. The point (x,y) for which $f(x,y) > T$ is referred to as an object point; otherwise, the point is referred to as a background point.

Segmentation Methods

With so many algorithms being created, classifying diverse picture segmentation approaches has become a necessary endeavor. Three types of segmentation algorithms have been identified:

1. Clustering or thresholding
2. Edge detection
3. Region extraction

Segmentation Modules

It is based on mathematical morphology and has three modules:

(a) Blood Vessels extraction

(b) Extraction of the hard exudates and optic disc

(c) Detection of the optic disc, which is used for distinguishing it from exudates.

3.5 IMPLEMENTATION OF KNN ALGORITHM:

By applying the two algorithm of the KNN (i.e. Eulicidean and Manhattan algorithm) we can get the different result based on the accuracy of the different model.

Here is the approach and the code that used to determine the prediction of diabetic retinopathic eye.

The K-Nearest Neighbour method is based on the Supervised Learning technique and is one of the most basic Machine Learning algorithms. The K-NN method assumes that the new case/data and existing cases are comparable and places the new case in the category that is most similar to the existing categories. The K-NN method saves all available data and classifies a new data point based on its similarity to the existing data. This implies that fresh data may be quickly sorted into a well-defined category using the K-NN method. The K-NN algorithm may be used for both regression and classification; however it is more commonly utilized for classification tasks. The K-NN algorithm is a non-parametric algorithm, which means it makes no assumptions about the underlying data.

It's also known as a lazy learner algorithm since it doesn't learn from the training set right away; instead, it saves the dataset and performs an action on it when it comes time to classify it.

During the training phase, the KNN algorithm simply stores the dataset, and when it receives new data, it classifies it into a category that is quite similar to the new data.

Consider the following scenario: We have a photograph of a creature that resembles both a cat and a dog, and we want to know if it is a cat or a dog. We may utilize the KNN method for this identification because it is based on a similarity measure. Our KNN model will look for features in the new data set that are comparable to those in the cats and dogs photos, and categorise it as either a cat or a dog based on the most similar features.

```
x_axis_k_points=[]

f1_euclidean=[]
accuracies_euclidean=[]
conf_matrix_euclidean=[]

for i in range(7):
  knn_euclidean=KNeighborsClassifier(n_neighbors=i+1)
  knn_euclidean.fit(train_data,train_label_list)


  pred_lables_euclidean=knn_euclidean.predict(test_feature)
  print(pred_lables_euclidean)


  acc_euclidean=knn_euclidean.score(test_feature,test_label)
  accuracies_euclidean.append(acc_euclidean)
  print(accuracies_euclidean)

  conf_matrix_euclidean.append(metrics.confusion_matrix(test_label,pred_lables_euclidean))
  print(conf_matrix_euclidean)

  f1_euclidean.append(metrics.f1_score(test_label,pred_lables_euclidean,pos_label='0'))
  print(f1_euclidean)
```

Figure 5: Implementation of KNN

```
       [0, 0]])]
[0.5714285714285715, 0.5714285714285715]
['0' '0' '1' '1' '1']
[0.4, 0.4, 0.4]
[array([[2, 3],
       [0, 0]]), array([[2, 3],
       [0, 0]]), array([[2, 3],
       [0, 0]])]
[0.5714285714285715, 0.5714285714285715, 0.5714285714285715]
['0' '0' '1' '1' '1']
[0.4, 0.4, 0.4, 0.4]
[array([[2, 3],
       [0, 0]]), array([[2, 3],
       [0, 0]]), array([[2, 3],
       [0, 0]]), array([[2, 3],
       [0, 0]])]
[0.5714285714285715, 0.5714285714285715, 0.5714285714285715, 0.5714285714285715]
['0' '0' '1' '1' '1']
[0.4, 0.4, 0.4, 0.4, 0.4]
[array([[2, 3],
       [0, 0]]), array([[2, 3],
       [0, 0]]), array([[2, 3],
       [0, 0]]), array([[2, 3],
       [0, 0]]), array([[2, 3],
       [0, 0]])]
[0.5714285714285715, 0.5714285714285715, 0.5714285714285715, 0.5714285714285715, 0.5714285714285715]
['0' '0' '1' '1' '1']
[0.4, 0.4, 0.4, 0.4, 0.4, 0.4]
[array([[2, 3],
       [0, 0]]), array([[2, 3],
       [0, 0]]), array([[2, 3],
       [0, 0]]), array([[2, 3],
       [0, 0]]), array([[2, 3],
       [0, 0]]), array([[2, 3],
       [0, 0]])]
[0.5714285714285715, 0.5714285714285715, 0.5714285714285715, 0.5714285714285715, 0.5714285714285715, 0.5714285714285715]
['0' '0' '1' '1' '1']
[0.4, 0.4, 0.4, 0.4, 0.4, 0.4, 0.4]
[array([[2, 3],
       [0, 0]]), array([[2, 3],
       [0, 0]]), array([[2, 3],
       [0, 0]]), array([[2, 3],
       [0, 0]]), array([[2, 3],
       [0, 0]]), array([[2, 3],
       [0, 0]]), array([[2, 3],
       [0, 0]])]
[0.5714285714285715, 0.5714285714285715, 0.5714285714285715, 0.5714285714285715, 0.5714285714285715, 0.5714285714285715, 0.5714285714285715]
```

```python
f1_manhattan=[]
accuracies_manhattan=[]
conf_matrix_manhattan=[]
for i in range(7):
  knn_manhattan=KNeighborsClassifier(n_neighbors=i+1,p=1)
  knn_manhattan.fit(train_data,train_label_list)


  pred_lables_manhattan=knn_manhattan.predict(test_feature)
  print(pred_lables_manhattan)


  acc_manhattan=knn_manhattan.score(test_feature,test_label)
  accuracies_manhattan.append(acc_euclidean)
  print(accuracies_manhattan)

  conf_matrix_manhattan.append(metrics.confusion_matrix(test_label,pred_lables_manhattan))
  print(conf_matrix_manhattan)

  f1_manhattan.append(metrics.f1_score(test_label,pred_lables_manhattan,pos_label='0'))
  print(f1_manhattan)
```

```
['0' '0' '1' '1' '1']
[0.4]
[array([[2, 3],
       [0, 0]])]
[0.5714285714285715]
```

Figure 6: Manhatten algorithm

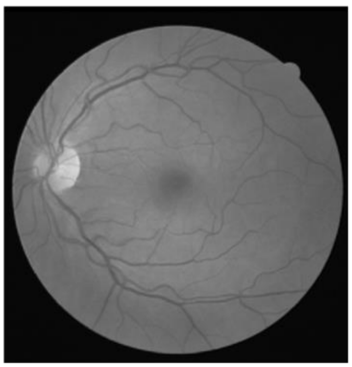
CHAPTER 4

RESULTS AND DISCUSSION

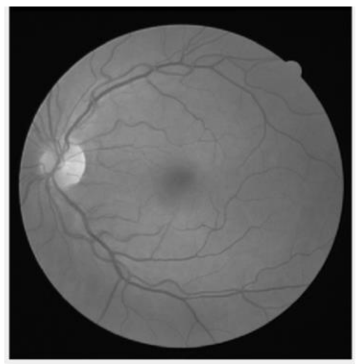
DRIVE, STARE, DIARETDB0, DIARETDB1 and MESSIDORdatabase[11][12] is considered for this experiment to investigate and analyze the effectiveness of all the algorithms All the experiments are performed using MATLAB2016 software and Google Collab.

(a) (b)

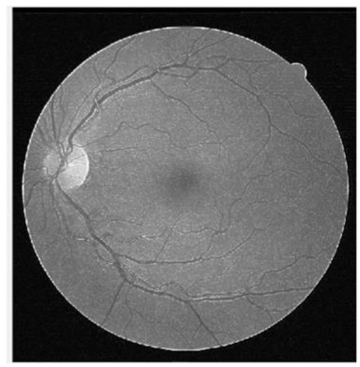
Figure 7: Fundus image of eye; (a) Original image (b) Greyscale image



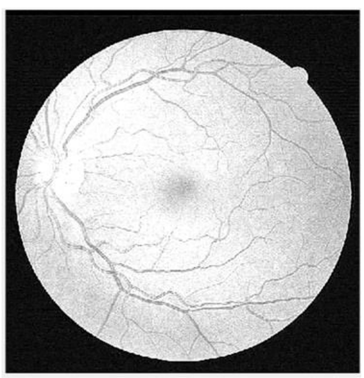
1.) BOX FILTER



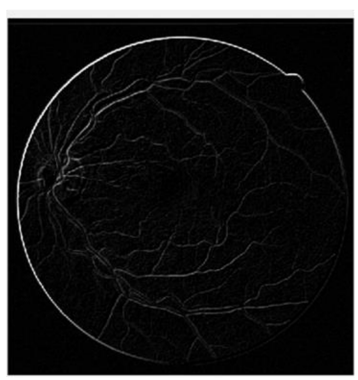
2.) WEIGHTED AVERAGE FILTER



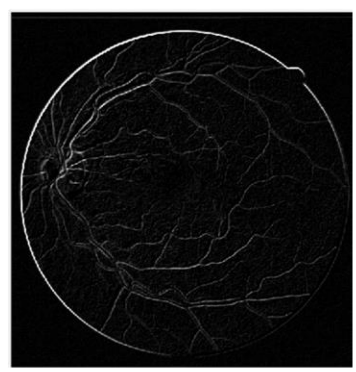
3.) LAPLACIAN FILTER



4.) HIGH BOOST FILTER



5.) PREWITT OPERATOR



6.) SOBEL OPERATOR

Figure 8: Various pre-processing filters

BLOOD VESSEL EXTRACTION

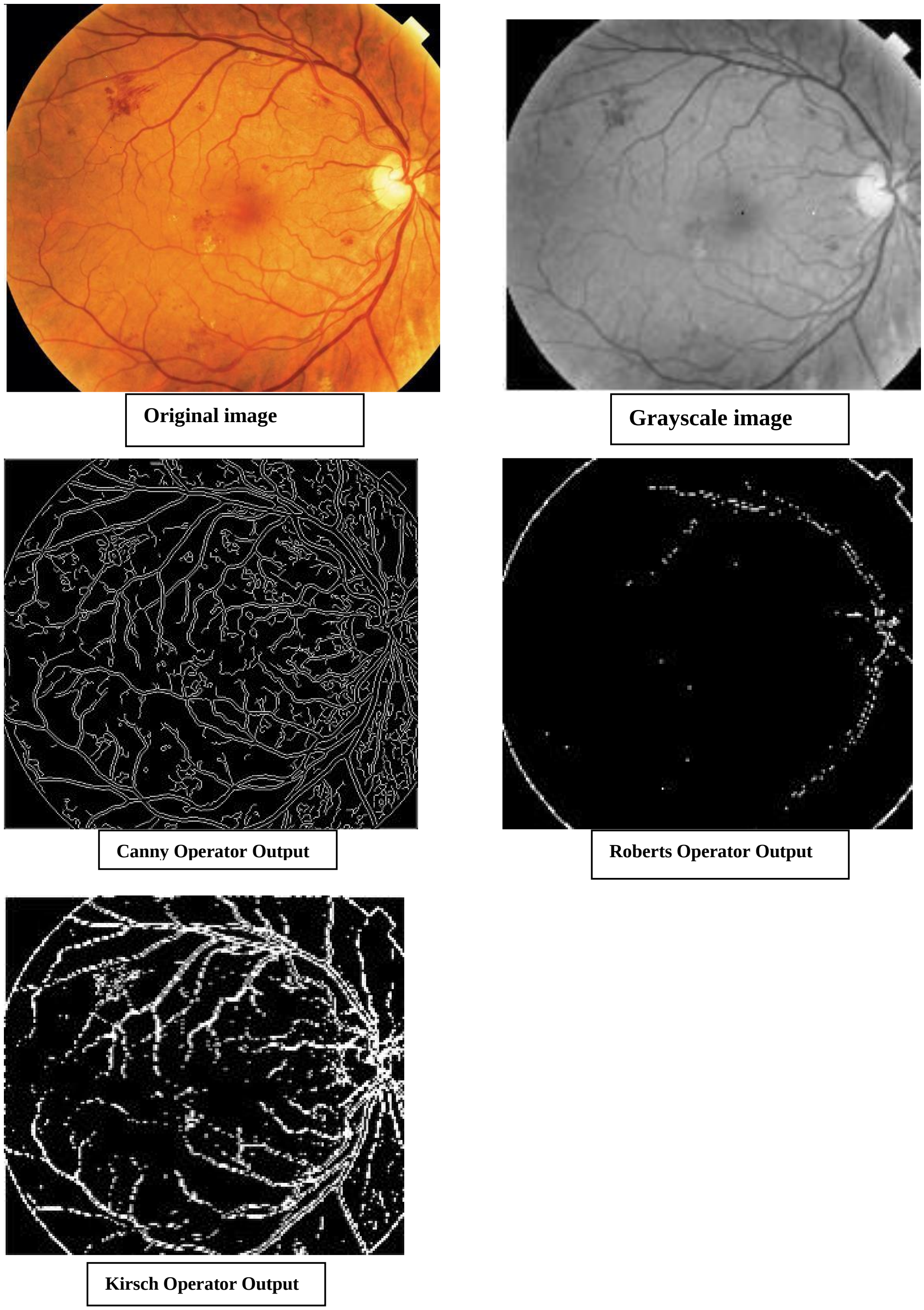


Figure 9: Extraction blood Vessel using various operators

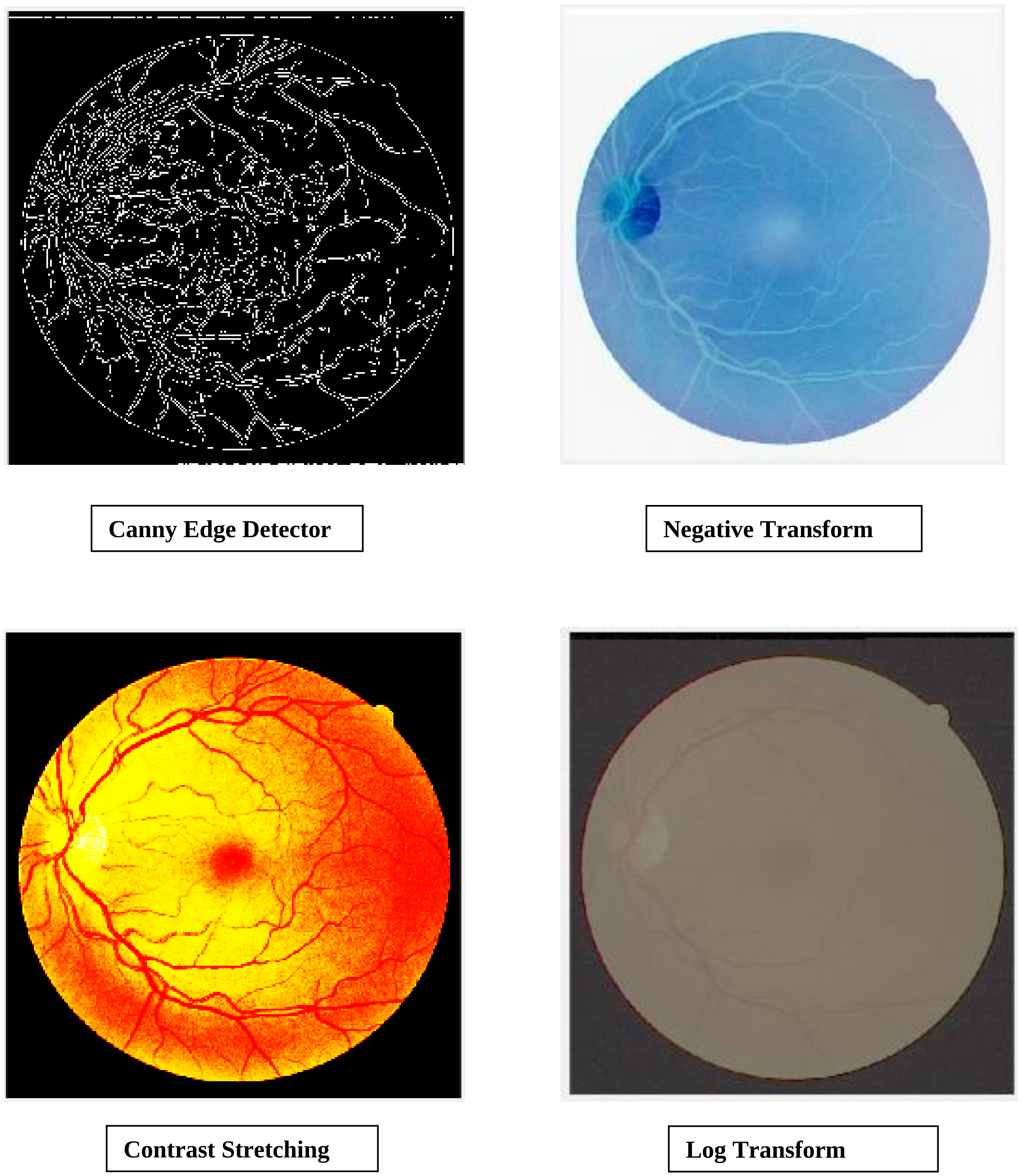
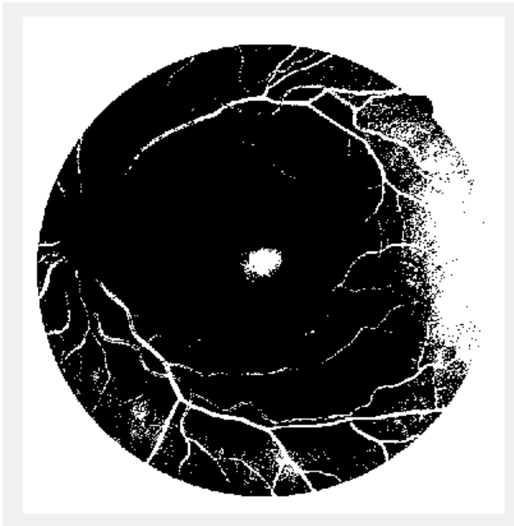
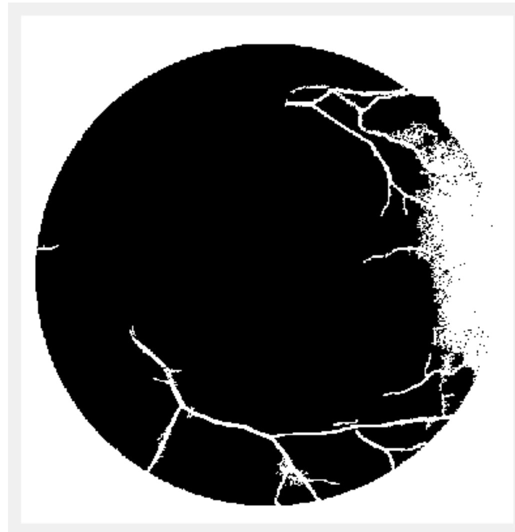


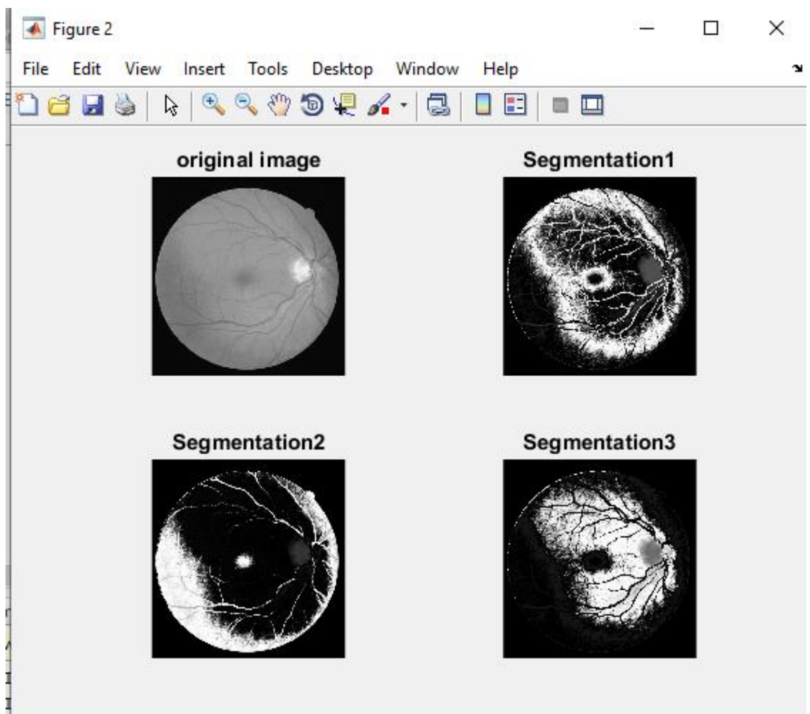
Figure 10: Detected and enhanced images using different operators





Thresholding

Extracting Blood Vessels



Fuzzy C mean

Figure 11: Segmentation of Vessels and Hard exudates.

Applying thresholding then applying BW label for connectivity and segmenting of data. At last applying fuzzy c mean for clustering the data.

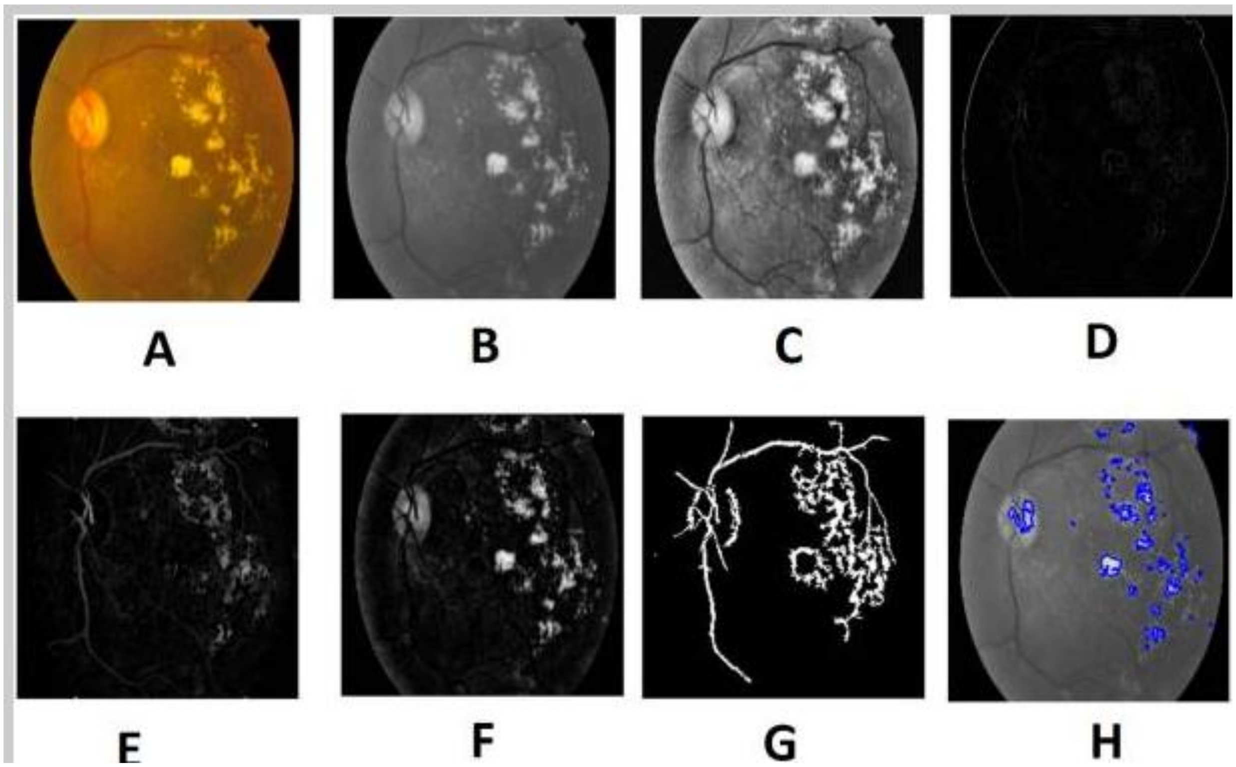


Figure 12: Preprocessed result of DR. (A) input image,(B) green channel,(C) histogram enhanced,(D) filtered image,(E) after bottom hat transform,(F) after top hat transform,(G) blood vessel segmented,(H) counters enhanced

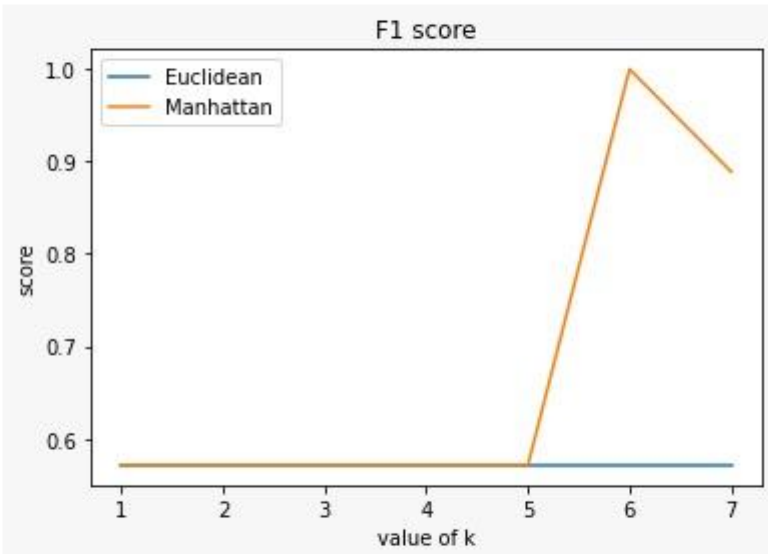


Figure 13: Plot between Euclidean algorithm and Manhattan algorithm

```
    print("OUTPUT : Diabetic Retinopathy Found")

Enter the path of the file: /content/drive/MyDrive/Colab Notebooks/vinayak/sample/test
Total images:  7
7
['0', '0', '0', '0', '0']
OUTPUT : Diabetic Retinopathy Not Found
OUTPUT : Diabetic Retinopathy Not Found
OUTPUT : Diabetic Retinopathy Found
OUTPUT : Diabetic Retinopathy Not Found
OUTPUT : Diabetic Retinopathy Not Found
OUTPUT : Diabetic Retinopathy Not Found
OUTPUT : Diabetic Retinopathy Not Found
```

Figure 14: Code Output for detecting Diabetic Retinopathy

Hence we are able to detect DR from fundus images of eye.

CHAPTER 5

CONCLUSION AND FUTURE WORK

Image segmentation algorithms perform well when compared to real-world approaches. Many elements, such as intensity, texture, and picture content, influence the outcome of image segmentation methods. A rapid and efficient approach for extracting blood vessels and hard exudates in a colour eye fundus picture was given in our study. The simulation findings on a retinal dataset show that the suggested approach may be used with retinal pictures and enhances the identification of blood vessels and hard exudates to decrease human error or give service in remote places. Our research study offers an important screening method for Diabetic Retinopathy early identification. The proposed method takes less time to compute and detects important clinical features of retinal images such as blood vessels, hard exudates, and optic disk.

To get better outcomes, future study should focus on exudate extraction by integrating unsupervised and supervised detection algorithms.

This methodology can also be performed by Deep Learning algorithms.

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PUBLICATIONS

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(ACCEPTED AND PRESENTED)