

DEEP MULTIPLE INSTANCE LEARNING FOR AUTOMATIC DETECTION OF DIABETIC RETINOPATHY IN RETINAL IMAGES

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Technology degree in **Biomedical Engineering**.

By

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**DEPARTMENT OF BIOMEDICAL ENGINEERING
SCHOOL OF BIO AND CHEMICAL ENGINEERING**

**SATHYABAMA
INSTITUTE OF SCIENCE AND
TECHNOLOGY**

(DEEMED TO BE UNIVERSITY)

**Accredited with Grade "A" by NAAC | 12B Status by UGC | Approved
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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **J. KAVITHA LAKSHMI (37240044)** and **M.K. GOMATHI BALA (37240081)** who carried out the project entitled on “**Deep Multiple Instance Learning for Automatic Detection of Diabetic Retinopathy in Retinal Images**” under my supervision from September 2020 to March 2021

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Guide and supervisor

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Submitted for Viva voce Examination held on_____

Internal Examiner

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DECLARATION

We, **KAVITHA LAKSHMI. J (37240044)** and **GOMATHI BALA.M.K. (37240081)**

hereby declare that the Project Report entitled “**Deep Multiple Instance Learning for Automatic Detection of Diabetic Retinopathy in Retinal Images**” done under the guidance of **Dr. ANIMA NANDA, Director, IQAC, Department of Biomedical Engineering** is submitted in partial fulfillment of the requirements for the award of **Bachelor of Technology degree in Biomedical Engineering**.

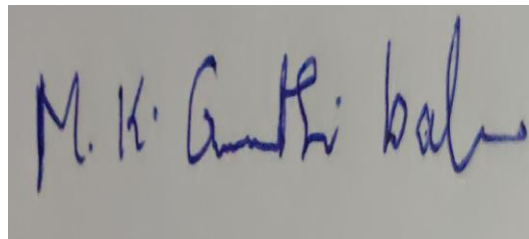
DATE:

PLACE:

1.

A handwritten signature in blue ink on a light-colored background. The signature reads "J. Kavitha Lakshmi" and is underlined. A small watermark "Scanned by TapScanner" is visible in the bottom right corner.

2.

A handwritten signature in blue ink on a light-colored background. The signature reads "M. K. Gomathi Bala".

SIGNATURE OF THE CANDIDATES

ACKNOWLEDGEMENT

We are pleased to acknowledge our sincere thanks to the Board of Management of **SATHYABAMA INSTITUTE OF SCIENCE AND TECHNOLOGY** for their kind encouragement in doing this project and for complete successfully.

At first we would like to express our indebtedness to the almighty for keeping us healthy in body and mind for successfully completing the project.

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Last but not least, we express my heartfelt gratitude to our beloved parents, and family members and friends, who have played an instrumental role in finishing my project to receive the degree.

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ABSTRACT

Clinical picture investigation could likewise be a truly trendy examination region in of late during which advanced pictures are dissected for the finding and screening of changed clinical issues. Diabetic retinopathy is one among the exceptional eye illnesses which will cause visual impairment and vision misfortune. DM, a problem, has become one of the quickly expanding wellbeing dangers both in India and around the world. Diabetic Retinopathy (DR) is an eye fixed illness brought about by the expansion of insulin in blood and will cause visual impairment. a programmed framework for the essential discovery of DR can save a patient vision and ought to likewise help the ophthalmologist in screening of DR which contains contrasting sorts of injury, i.e., miniature aneurysms, hemorrhages, exudates. Early finding by customary screening and treatment is valuable in forestalling visual imperfection and visual impairment. This task presents how for discovery and arrangement of exudates in hued retinal pictures. It disposes of the replication exudates district by eliminating the vulnerable side area. A few picture preparing strategies including Image Enhancement, Segmentation, Classification, and enrollment has been produced for the essential identification of DR on the possibility of highlights like veins, radiates, hemorrhages and miniature aneurysms. This venture presents an audit of most recent work on the usage of picture handling strategies for DR include identification. Picture Processing procedures are assessed on the possibility of their outcomes. Exudates are discovered utilizing their high dim level variety, and in this manner the grouping of exudates is finished with exudates highlights and SVM classifier.

Keywords: *Diabetic retinopathy, Hemorrhages ,exudates ,retinal pictures, image enhancement, classification and segmentation.*

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LIST OF ABBREVIATIONS

DR	Diabetic retinopathy
PDR	Proliferative retinopathy
NPDR	Non proliferative retinopathy
DRiDB	Diabetic retinopathy image database
GLCM	Grey level co-occurrence matrix
ROI	Region of interest
HE	Hemorrhages
CT	Computed tomography
PET	Positron emission tomography
SPECT	Single photo emission computerized tomography
MATLAB	Matrix laboratory
MSE	Mean square error
PSNR	Peak signal to noise ratio
AD	Average difference
MD	Maximum difference
MAE	Mean absolute error
NK	Normalized cross-correlation
SC	Structural content
MMSE	Minimum mean square error

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CHAPTER 1

INTRODUCTION

1.1 OUTLINE OF PROJECT:

1.1.1 DIABETIC RETINOPATHY:

Diabetic retinopathy, additionally referred to as diabetic disease (DED), may be a medical condition within which injury happens to the tissue layer because of DM. it's a number one reason behind sightlessness in developed countries. Diabetic retinopathy affects up to eighty p.c of these UN agency have had polygenic disorder for twenty years or a lot of. a minimum of ninetieth of latest cases might be reduced with correct treatment and watching of the eyes. The longer an individual has polygenic disorder, the upper his or her possibilities of developing diabetic retinopathy annually within the us, diabetic retinopathy accounts for twelve-tone music of all new cases of sightlessness. it's additionally the leading reason behind sightlessness in individuals aged twenty to sixty four.

1.1.2 Symptoms of diabetic retinopathy:

- gradually worsening vision.
- sudden vision loss.
- shapes floating in your field of vision (floaters)
- blurred or patchy vision.
- eye pain or redness.

1.1.3 Causes:

Diabetic retinopathy is caused by prolonged high glucose levels Over time, high sugar aldohexose levels will weaken and injury the little blood vessels inside the membrane. This may cause haemorrhages, exudates and even swelling of the membrane. This then starves the membrane of atomic number 8, and abnormal vessels could grow. smart glucose management helps to lower polygenic disorder retinopathy risks. If associate degree of the below have an effect on you it's price having an retinopathy screening examination as quickly as attainable. Poor glucose

management, Protein in excreta, High vital sign Prolonged polygenic disorder Raised fats (triglycerides) within the blood Anyone laid low with polygenic disorder faces the danger of developing diabetic retinopathy and alternative polygenic disorder complications.

1.1.4 Techniques:

In our proposed project, we will develop automatic detection of diabetic retinopathy which is high in image quality In device learning, multiple-example learning (MIL) is a sort of supervised learning. Instead of receiving a hard and fast of times which might be for my part categorized, the learner gets a hard and fast of categorized luggage, every containing many times. In the easy case of multiple-example binary classification, a bag can be categorized bad if all of the times in it are bad. On the alternative hand, a bag is categorized high quality if there's as a minimum one example in it that's high quality. From a group of categorized luggage, the learner attempts to either (i) set off a idea with the intention to label person times efficaciously or (ii) discover ways to label luggage with out inducing the idea.

CHAPTER 2

LITERATURE REVIEW

Snehal Dilip Kasurde and S.N.Randive (2015) proposed the technique that Proliferative Diabetic Retinopathy (PDR) is a phase of retinopathy where veins multiply for example develops. The sign of PDR is neovascularization, the development of unusual new vessels. Here, first vessel division is finished by changing over picture into double picture. So vessel and nonvessel part is separated. By utilizing morphological activity and organizing component as line, straight vessels are recognized and taken out. So remaining part is new vessels. These morphological tasks are taken for various directions like 45° , 90° , 135° , 180° . Straight vessels were taken out to recognize new vessels from typical vasculature. Morphological diminishing is utilized to thin just new vessels. Highlight extraction is finished by windowing picture into 50 by 50 to figure number of vessel pixels in each window. In the event that quantities of vessel pixels are more prominent than edge esteem, PDR is recognized.

Narjes Karami and Hossein Rabbani (2017) presented a word reference learning (DL) based technique for programmed location of DR in advanced fundus pictures. The recognition strategy is as indicated by best nuclear portrayal of fundus pictures dependent on educated word references by KSVD calculation. Nonetheless, the learned word references by KSVD ought to have the option to segregate the typical and diabetic classes, for example discriminative particles ought to be planned. For this reason, the best discriminative molecules are gotten for nuclear portrayal of pictures in each class. The arrangement rule depends on the best meager portrayal, for example the test picture is had a place with the class with least number of best explicit molecules. Our discriminative DL put together strategy was tried with respect to 30 shading fundus pictures which of 70% and 90% were acquired for ordinary and diabetic pictures, individually.

Asti Herliana et al. (2018) proposed All together for this sickness to be recognized early, a precise arrangement technique is required. Information mining idea is one option in directing arrangement. This examination was leading by applying molecule swarm streamlining (PSO) strategy to choose the best Diabetic Retinopathy include dependent on diabetic retinopathy dataset. At that point, the chose include is additionally ordered utilizing arrangement strategy for neural organization. The examination result show that there is an expansion in outcome by applying neural organization based molecule swarm improvement (PSO) of 76.11%. This examination likewise show that there is an increment in characterization result by utilizing highlight choice strategy for 4.35% from past aftereffect of 71.76% by just applying neural organization technique Sources.

Shailesh Kumar and Basant Kumar (2018) presents an improved diabetic retinopathy identification conspire by extricating exact zone and number of microaneurysm from shading fundus pictures. Customary screening of eye is essential for discovery and managing diabetic retinopathy. Diabetic retinopathy (DR) is an eye infection which happens because of harm of retina because of long ailment of diabetic mellitus. Microaneurysms (MA) are minuscule red spots on retina, formed by swelling out of delicate piece of the veins. The acknowledgment of MA at essential stage is vital and it is the initial phase in hindering DR. An assortment of strategies have been proposed for recognition and analysis of DR. In this paper, there are two highlights in particular; number and territory of MA have been resolved. At first, pre preparing procedures like green channel extraction, histogram leveling and morphological cycle have been utilized. For recognition of microaneurysms, head part investigation (PCA), contrast restricted versatile histogram leveling (CLAHE), morphological interaction, averaging separating have been utilized. Grouping of DR has been finished by straight Support vector machine (SVM).

Pavle Prenta et al. (2013) presented an outline of right now accessible information bases and present another diabetic retinopathy dataset. Our data set is as far as anyone is concerned the sole information base which has diabetic retinopathy pathologies and significant fundus structures explained for each picture from the data

set which makes it ideal for plan and assessment of as of now accessible and new picture preparing calculations for early discovery of diabetic retinopathy utilizing shading fundus pictures.

Morium Akter et al. (2014) proposed Retinopathy is a diabetic related inconvenience and fundamental driver of vision loss of the diabetic patients. Exudates are the significant indication of diabetic retinopathy. This paper presents a morphology based technique for the recognition of diabetic retinopathy through exudates from shading fundus pictures. We applied our methodology on fundus pictures and got agreeable outcomes, which are contrasted and the ophthalmologists' hand drawn ground facts.

Z. A. Omar et al. (2017) proposed a calculation that comprises of DR identification technique with the plan to improve the exactness of the current frameworks. The strategies used to distinguish DR highlights, to be specific exudates, hemorrhages and veins can be ordered into a few stages which are picture pre preparing, vessel and hemorrhages identification, optic plate evacuation and exudate discovery. Notwithstanding, the identification for vein and hemorrhages was performed all the while because of comparable force qualities. The proposed calculation was prepared and tried utilizing 49 and 89 fundus pictures, individually. The pictures utilized in preparing were acquired from Hospital Serdang, Malaysia while pictures utilized in the testing were gotten from DIARETDB1 information base. The entirety of the pictures were classified into four DR stages, in particular gentle Non Proliferative Diabetic Retinopathy (NPDR), moderate NPDR, extreme NPDR and Proliferative Diabetic Retinopathy (PDR). The pictures were caught under different brightening conditions. In the testing, the outcome shows that the level of location for vein and hemorrhages, and exudates are 98% and 100%, individually.

Mohammed.Y. Esmail et al. (2018) proposed Diabetic retinopathy is a diabetes inconvenience modify the retinal microvasculature. As diabetic results on retinopathy may cause no unmistakable manifestations or just gentle vision issue, the method of obtain retina picture is modern and just at eye center, this examination proposed to

plan straightforward optical framework with help of cell phone camera and a Webbased telemedicine framework for diabetic retinopathy screening. The Webput together framework was worked with respect to PHP programming language and My SQL for information base administration framework. The consequence of secure retina picture with the proposed system is accomplished and send through website page for additional examination by ophthalmic subject matter expert.

Masoud Khazaei Fadafe et al. (2018) presented that the AUC of the proposed strategy was 0.9012, which in examination with different techniques is the most elevated worth, demonstrating the legitimate capacity of this strategy in deciding the rightness of picture saliencies. End: The positive outcomes from the proposed calculation, which depend on picture handling strategies and roused by the human visual framework, recommend that utilizing this technique can assist ophthalmologists with diagnosing quick, exact, and solid diabetic retinopathy.

Kumar Parasuraman et al. (2018) proposed Retinal vascular is split utilizing the intricacy between the veins and incorporating establishment. Release hopefuls were perceived using thickness assessment and bobbing box techniques. Finally, game plan of the unmistakable periods of eye affliction was done using Random Forests technique considering the region and line of the veins and hemorrhages. The count has been taken a stab at a little picture data base and differentiated.

CHAPTER 3

AIM AND OBJECTIVE

3.1 AIM:

- To find diseased eye from the collected retinal images.
- To detect the stages of diabetic retinopathy early.

3.2 OBJECTIVE:

- To distinguish and group shade of retinal pictures.
- To improve pictures by different picture handling strategies.
- Portion to arrange pictures
- To distinguish or create strategy for early recognition of diabetic retinopathy (DR) or the premise of highlights, for example, veins, oozes, hemorrhages and miniature aneurysms.
- To assess picture handling information dependent on exudates highlights and SVM classifier.

3.2 EXISTING SYSTEM:

Narjes Karami[1] and Hossein Rabbani[1] A computer-aided screening and grading system depends on the automated detection of lesions. complex body part pictures with DR exhibit red lesions, like small aneurysms (MA) and hemorrhages (HE), and bright lesions, like exudates and cotton spots. The Existing technique takes as input a color complex body part image at the side of the binary mask of its region of interest (ROI).The ROI is that the circular space encircled by a black background. It outputs a likelihood color map for red lesion detection. The method contains six steps. First, spacial activity is applied to support completely different image resolutions. Second, the input image is preprocessed via smoothing and standardization. Third, the point (OD) is mechanically detected, to discard this space from the lesion detection.

3.2.1 DISADVANTAGES:

- The prediction of Retinopathy is quite difficult
- Segmentation methodology could manufacture unwanted noise.

- PSNR worth is high
- Image Assessment analysis provides poor performance.
- Segmentation covers unwanted region

3.3 PROPOSED SYSTEM:

Diabetic Retinopathy cause changes in eye harm the vessel. Image can bear a regular methodology of applying image process that include image acquisition, pre-processing like filtering (Median/Wiener/Gaussian), contrast improvement (Histogram Equalization/Adaptive Histogram), feature extraction like GLCM, Region Properties Image Assessment techniques followed by actual identification of disease. We will use Skin locus model and color bar graph for classification of the retinal pictures into class of traditional. the classification rate of the projected system can offer the higher potency and accuracy of distinguishing the malady with regard to existing systems.

3.3.1 ADVANTAGES:

- Retinopathy Prediction is Helps stop vision loss by early detection
- Automated vessel Extraction algorithms will save time, patients' vision and medical prices.
- Error likely low
- PSNR worth is incredibly low when put next to existing system.
- Adaptive bar graph provides brightness and intensity to section disease properly.

3.3 WORKFLOW:

- Image will undergo a standard method of applying image processing which include
- image acquisition,
- Pre-processing like filtering(Median/Wiener),
- contrast enhancement (Histogram Equalization/Adaptive Histogram),
- Feature extraction like GLCM,
- Region Properties
- Image Assessment techniques followed by exact identification of disease.
- We will use Skin locus model and color histogram for classification of the retinal images into category of Normal.

CHAPTER 4

MATERIALS AND METHODS

4.1 BLOCK DIAGRAM:

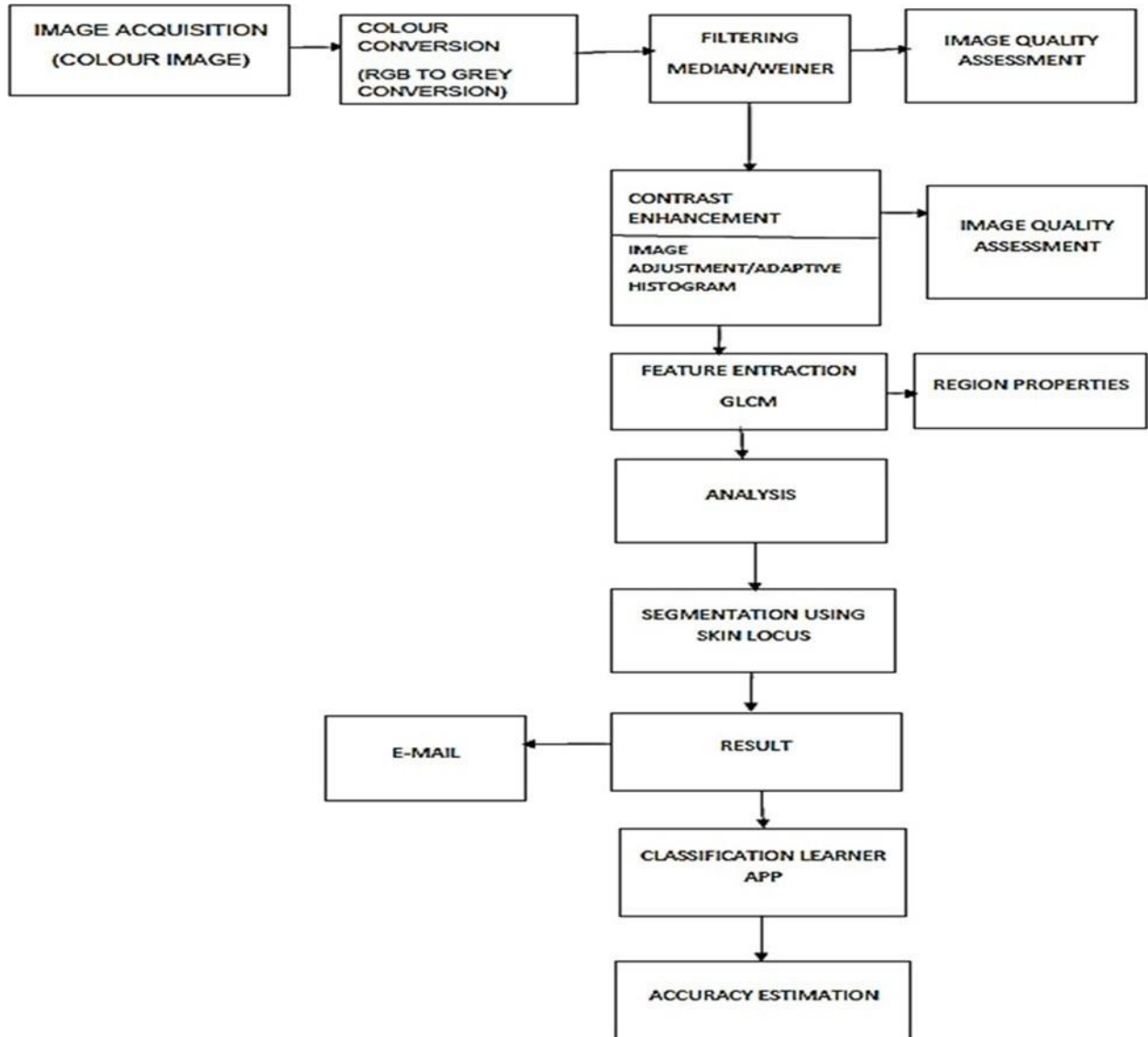


FIG 4.1 BLOCK DIAGRAM

4.2 EXPLANATION:

4.2.1 IMAGE ACQUISITION:

The first stage of any vision system is that the image acquisition stage. once the image has been obtained, numerous ways of process will be applied to the image to perform the various completely different vision tasks needed these days. However, if the image has not been nonheritable satisfactorily then the meant tasks might not be possible, even with the help of some sort of image sweetening. Digital imaging or digital image acquisition is that the creation of a digitally encoded illustration of the visual characteristics of associate degree object, like a physical scene or the inside structure of associate degree object. The term is commonly assumed to imply or embody the process, compression, storage, printing, and show of such pictures. A key advantage of a digital image, versus associate degree analog image like a movie photograph, is that the ability create copies and copies of copies digitally indefinitely with none loss of image quality.

Digital imaging will be classified by the kind of nonparticulate radiation or different waves whose variable attenuation, as they undergo or replicate off objects, conveys the data that constitutes the image. altogether categories of digital imaging, the data is regenerate by image sensors into digital signals that square measure processed by a pc and created output as a visible-light image. for instance, the medium of visible radiation permits photography (including digital videography) with numerous styles of digital cameras (including digital video cameras). X-rays permit digital X-ray imaging (digital radiography, radioscopy, and CT), and gamma radiations permit digital gamma ray imaging (digital scintigraphy, SPECT, and PET). Sound permits sonography (such as medical ultrasonography) and navigational instrument, and radio waves permit microwave radar. Digital imaging lends itself well to image analysis by software system, further on image redaction (including image manipulation).



FIG 4.2.1 INPUT IMAGE

4.2.2 GRAY IMAGE:

In photography, computer-generated representational process, and quantitative chemical analysis, a grayscale or greyscale image is one within which the worth of every pel may be a single sample representing solely AN quantity of sunshine, that is, it carries solely intensity info. Grayscale pictures, a form of black-and-white or grey monochrome, aer composed solely of reminder grey. The distinction ranges from black at the weakest intensity to white at the strongest.

Grayscale pictures are distinct from one-bit bi-tonal black-and-white pictures that, within the context of laptop imaging, are pictures with solely 2 colors: black and white (also referred to as bilevel or binary images). Grayscale pictures have several reminder grey in between.

Grayscale pictures are often the results of measurement the intensity of sunshine at every pel in keeping with a specific weighted combination of frequencies (or wavelengths), and in such cases they're monochromatic correct once solely one frequency (in follow, a slender band of frequencies) is captured. The frequencies will in theory be from anyplace within the spectrum (e.g. infrared, actinic radiation, ultraviolet, etc.) A quantitative analysis (or additional specifically photometric) grayscale image is a picture that features a outlined grayscale colorspace, that maps the hold on numeric sample values to the achromatic channel of a regular colorspace, that itself is predicated on measured properties of human vision. If the initial color image has no outlined, or if the grayscale image isn't meant to own human-perceived achromatic intensity because the color image has no distinctive mapping from such a color image to grayscale image.

4.2.3. Grayscale As Single Channels Of Multichannel Color Images:

Color pictures square measure usually engineered of many stacked color channels, every of them representing price levels of the given channel. for instance, RGB pictures square measure composed of 3 freelance channels for red, inexperienced and blue primary color components; CMYK pictures have four channels for cyan, magenta, yellow and black ink plates, etc. Here is Associate in Nursing example of color channel cacophonous of a full RGB color image. The column at left shows the isolated color channels in natural colours, whereas at right there square measure their grayscale equivalences:

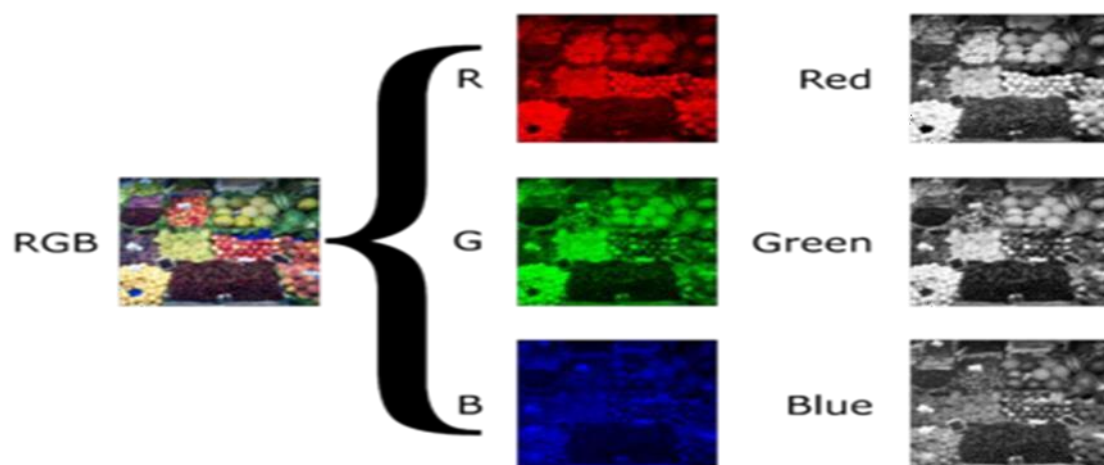


FIG 4.2.1.1 CONVERSION OF RGB TO GREY

The reverse is additionally possible: to create a full color image from their separate grayscale channels. By mangling channels, mistreatment offsets, rotating and different manipulations, inventive effects are often achieved rather than accurately reproducing the initial image.

4.2.4 MEDIAN FILTER:

The Median Filter could be a nonlinear digital filtering technique, usually wont to take away noise from a picture or signal. Such noise reduction could be a typical pre-processing step to enhance the results of later process (for example, edge detection on Associate in Nursing image). Median filtering is incredibly wide utilized in digital image process as a result of, beneath bound conditions, it preserves edges whereas removing noise (but see discussion below), additionally having applications in signal process.

4.2.5 WIENER FILTER:

In signal process, the Wiener filter could be a filter wont to turn out Associate in Nursing estimate of a desired or target random method by linear time-invariant (LTI) filtering of Associate in Nursing determined blatant method, presumptuous best-known stationary signal and noise spectra, and additive noise. The Wiener filter minimizes

the mean sq. error between the calculable random method and therefore the desired method.

4.2.5.1 DESCRIPTION:

The goal of the Wiener filter is to calculate a applied mathematics estimate of Associate in Nursing unknown signal employing a connected signal as Associate in Nursing input Associate in Nursingd filtering that best-known signal to supply the estimate as an output. for instance, the best-known signal would possibly carries with it Associate in Nursing unknown signal of interest that has been corrupted by additive noise. The Wiener filter are often wont to separate out the noise from the corrupted signal to produce Associate in Nursing estimate of the underlying signal of interest. The Wiener filter is predicated on a applied mathematics approach, and a a lot of applied mathematics account of the speculation is given within the minimum mean sq. error (MMSE) reckoner article. Typical settled filters square measure designed for a desired frequency response. However, the look of the Wiener filter takes a distinct approach. One is assumed to possess information of the spectral properties of the initial signal and therefore the noise, and one seeks the linear time-invariant filter whose output would come back as about to the initial signal as potential. Wiener filters square measure characterised by the following:

- **Assumption:** signal and (additive) noise square measure stationary linear random processes with best-known spectral characteristics or best-known autocorrelation and cross-correlation
- **Requirement:** the filter should be physically realizable/causal (this demand are often born, leading to a non-causal solution)
- **Performance criterion:** minimum mean-square error (MMSE) This filter is often utilized in the method of deconvolution; for this application.

4.2.6 GRAY LEVEL CO-OCCURRENCE MATRIX:

Feature extraction involves simplifying the number of resources needed to explain an oversized set of information accurately. When playing analysis of complicated knowledge one among the major problems stems from the amount of variables concerned. Analysis with an oversized range of variables typically needs a large amount of memory and computation power or a classification algorithm that over fits the coaching sample and generalizes poorly to new samples. Feature extraction could be a general term for methods of constructing mixtures of the variables to get around these issues whereas still describing the information with sufficient accuracy. Texture tactile or visual characteristic of a surface. Texture analysis aims find distinctive singular novel means of representing the underlying characteristics of textures and represent them in some easier however unique type, in order that they can be used for strong, correct classification and segmentation of objects. although texture plays a big role in image analysis and pattern recognition, solely many architectures implement aboard textural feature extraction. during this paper, grey level cooccurrence matrix is developed to get applied mathematics texture features. variety of texture options could also be extracted from the GLCM. solely four second order options particularly angular second moment, correlation, inverse distinction moment,

and entropy are computed. These four measures give high discrimination accuracy needed for picture estimation.

4.2.6.1 CORRELATION:

It passes the calculation of the correlation of a pixel and its neighbor over the whole image means it figures out the linear dependency of gray levels on those of neighbouring pixels. On behalf a perfectly positively or negative correlated image, the correlation value is 1 and -1. On behalf of constant image its value is NaN. Range=[-1,1] and the formula is

$$Correlation = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i - \mu)(j - \mu)}{\sigma^2}$$

4.2.6.2 CONTRAST:

It passes the calculation of the correlation of a pixel and its neighbor over the whole image means it figures out the linear dependency of gray levels on those of neighbouring pixels. On behalf a perfectly positively or negative correlated image, the correlation value is 1 and -1. On behalf of constant image its value is NaN..Range=[-1,1] and the formula is

$$Contrast = \sum_{i,j=0}^{N-1} P_{ij} (i - j)^2$$

4.2.6.3 ENERGY:

Since energy is used for doing work, Thus orderliness. It makes use for the texture that calculates orders in an image. It gives the sum of square elements in GLCM. It is fully different from entropy. When the window is proficient orderly, energy value is high. The square root of ASM(Angular Second Moment) texture character is used as Energy. Its range is [0 1]. Since constant image its value is 1. The equation energy is

$$Energy = \sum_{i,j=0}^{N-1} (P_{ij})^2$$

4.2.6.4 HOMOGENITY:

In short term it is going by the name of HOM. It passes the value that calculates the tightness of distribution of the elements in the GLCM to the GLCM diagonal. For diagonal GLCM its value is 1 and its range is [0,1]. Opposite of contrast weight is homogeneity weight values, with weight decreases exponentially loose from the

diagonal. The weight employed in contrast is $(i-j)^2$ and in homogeneity ,it is $1/(1+(i-j)^2)$.The equation is

$$Homogeneity = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2}$$

where:

P_{ij} - Element i, j of the normalized symmetrical GLCM

N - Number of gray levels in the image as specified by Number of levels in under Quantization on the GLCM texture page of the Variable Properties dialog box.

C - The Correlation feature $\text{sgn}(x)$ - Sign of a real number

- $x = -1$ for $x < 0$
- $x = 0$ for $x = 0$
- $x = 1$ for $x > 0$

σ^2 - The variance of the intensities of all reference pixels in the relationships that contributed to the GLCM, calculated as:

Note: This may approximate, but is not identical to, the variance of the intensities of all the pixels in the data window W (as defined by the GLCM algorithm), and it is dependent upon the choice of spatial relationship in that algorithm.

μ - the GLCM mean (being an estimate of the intensity of all pixels in the relationships that contributed to the GLCM), calculated as:

Note: This also approximates, but is not identical to, the mean of all the pixels in the data window W (as defined by the GLCM algorithm), and it is dependent upon the choice of spatial relationship in that algorithm

4.2.6.5 HISTOGRAM EQUALISATION:

This method 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.

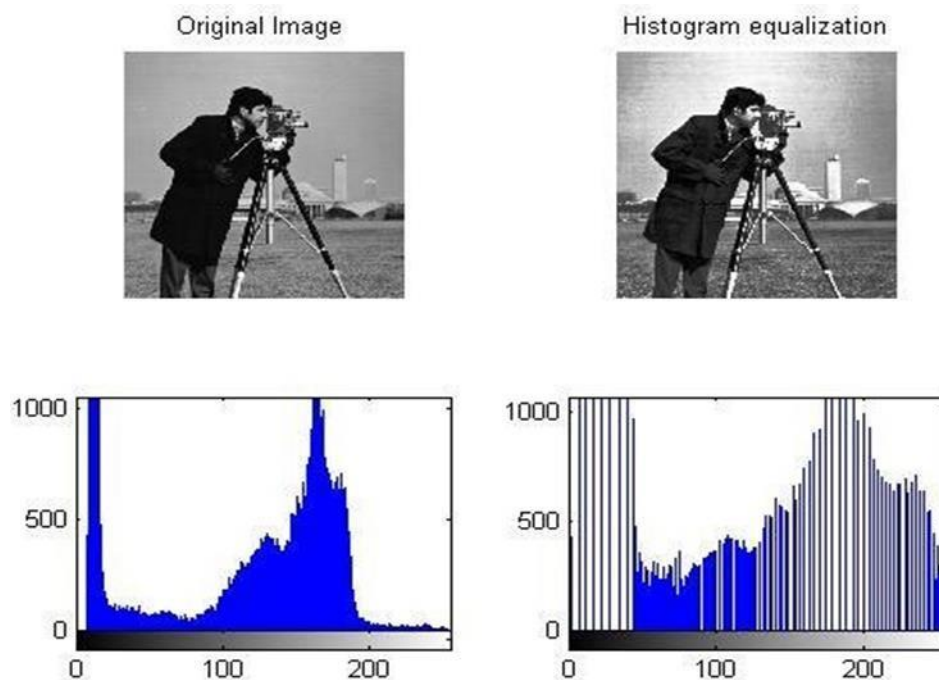


FIG 4.3.5 HISTOGRAM EQUALIZATION

4.2.6.6 ADAPTIVE HISTOGRAM EQUALISATION:

Adaptive histogram equalization (AHE) is a computer image processing technique used to improve contrast in images. 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.

However, AHE has a tendency to over amplify noise in relatively homogeneous regions of an image. A variant of adaptive histogram equalization called contrast limited adaptive histogram equalization (CLAHE) prevents this by limiting the amplification

4.2.6.7 IM2BW (BLACK AND WHITE IMAGE):

- It converts an image to a binary image, based on threshold.
- Im2bw produces binary images from indexed, intensity, or RGB images. To do this, it converts the input image to grayscale format (if it is not already an intensity image), and then converts this grayscale image to binary by

thresholding. The output binary image BW has values of 0 (black) for all pixels in the input image with luminance less than level and 1 (white) for all other pixels. (Note that you specify level in the range [0,1], regardless of the class of the input image.)

- `BW = im2bw (I, level)` converts the intensity image I to black and white.
- `BW = im2bw (X, map, level)` converts the indexed image X with colormap map to black and white.
- `BW = im2bw (RGB, level)` converts the RGB image RGB to black and white.

4.2.7 IMAGE QUALITY ASSESSMENT:

Measurement of image quality is important for many image processing applications. Image quality assessment is closely related to image similarity assessment in which quality is based on the differences (or similarity) between a degraded image and the original, unmodified image. There are two ways to measure image quality by subjective or objective assessment. Subjective evaluations are expensive and time-consuming. It is impossible to implement them into automatic real-time systems. Objective evaluations are automatic and mathematically defined algorithms. Subjective measurements can be used to validate the usefulness of objective measurements. Therefore objective methods have attracted more attention in recent years.

Well-known objective evaluation algorithms for measuring image quality include mean squared error (MSE) and peak signal-to-noise ratio (PSNR). MSE & PSNR are very simple and easy to use.

Measurement of image quality is crucial to many image processing systems. Due to inherent physical limitations and economic reasons, the quality of images and videos could visibly degrade right from the point when they are captured to the point when they are viewed by a human observer. Identifying the image quality measures that have highest sensitivity to these distortions would help systematic design of coding, communication and imaging systems and of improving or optimizing the image quality for a desired quality of service at a minimum cost.

There are large varieties of these metrics. Some of existing measures of image quality are listed below.

4.2.7.1 Mean Squared Error (MSE):

One obvious way of measuring this similarity is to compute an error signal by subtracting the test signal from the reference, and then computing the average energy of the error signal. The mean-squared-error (MSE) is the simplest, and the most widely used, full-reference image quality measurement. This metric is frequently used in signal processing and is defined as follows

$$MSE = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (x(i, j) - y(i, j))^2$$

Where $x(i, j)$ represents the original (reference) image and $y(i, j)$ represents the distorted (modified) image and i and j are the pixel position of the $M \times N$ image. MSE is zero when $x(i, j) = y(i, j)$.

4.2.7.2 Peak Signal to Noise Ratio (PSNR):

The PSNR is evaluated in decibels and is inversely proportional the Mean Squared Error. It is given by the equation.

$$PSNR = 10 \log_{10} \frac{(2^n - 1)^2}{\sqrt{MSE}}$$

4.2.7.3 Average Difference:

AD is simply the average of difference between the reference signal and test image. It is given by the equation. This metric is frequently used in signal processing and is defined as follows

$$AD = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (x(i, j) - y(i, j))$$

4.2.7.4 Maximum Difference:

MD is the maximum of the error signal (difference between the reference signal and test image).

$$MD = MAX|x(i, j) - y(i, j)|$$

4.2.7.5 Mean Absolute Error:

MAE is average of absolute difference between the reference signal and test image. It is given by the equation.

$$MAE = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N |x(i, j) - y(i, j)|$$

4.2.7.6 Normalized Cross-Correlation (NK):

The closeness between two digital images can also be quantified in terms of correlation function. Normalized Cross-Correlation (NK) measures the similarity between two images and is given by the equation

$$NK = \frac{\sum_{i=1}^M \sum_{j=1}^N (x(i, j) \times y(i, j))}{\sum_{i=1}^M \sum_{j=1}^N (x(i, j))^2}$$

4.2.7.7 Structural Content:

SC is also correlation based measure and measures the similarity between two images. Structural Content (SC) is given by the equation

$$SC = \frac{\sum_{i=1}^M \sum_{j=1}^N (y(i, j))^2}{\sum_{i=1}^M \sum_{j=1}^N (x(i, j))^2}$$

Where $x(i, j)$ represents the original (reference) image and $y(i, j)$ represents the distorted (modified) image. The simplest and most widely used full-reference image quality measure is the MSE and PSNR. These are appealing because they are simple to calculate, have clear physical meanings, and are mathematically convenient in the context of optimization. MSE and PSNR lack a critical feature: the ability to assess image similarity across distortion types. They both have low computational complexities. MSE and PSNR are acceptable image similarity measures when the images in question differ by simply increasing distortion of a certain type. These mathematical measures fail to capture image quality when they are used to measure across distortion types. MSE and PSNR do not model the human visual system.

Advantage of MSE and PSNR are that they are very fast and easy to implement. However, they simply and objectively quantify the error signal. With PSNR, greater values indicate greater image similarity.

4.2.8 Image Segmentation:

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as image objects). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics.

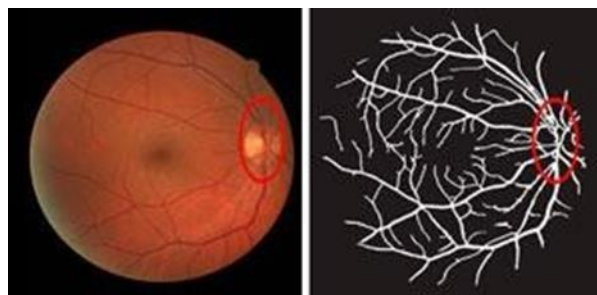


FIG 4.4 IMAGE SEGMENTATION

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s). When applied to a stack of images, typical in medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like marching cubes.

4.2.8.1 SKIN LOCUS:

In computer vision, image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super-pixels). The goal of

segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze.

4.2.8.2 MORPHOLOGICAL OPERATION:

Morphology is a technique of image processing based on shapes. The value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. By choosing the size and shape of the neighborhood, you can construct a morphological operation that is sensitive to specific shapes in the input image.

4.2.8.3 DILATION & EROSION :

Dilation and erosion are two fundamental morphological operations. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the structuring element used to process the image.

4.2.8.4 Morphological Reconstruction:

Morphological reconstruction is another major part of morphological image processing. Based on dilation, morphological reconstruction has these unique properties:

Processing is based on two images, a marker and a mask, rather than one image and a structuring element

- Processing repeats until stability; i.e., the image no longer changes
- Processing is based on the concept of connectivity, rather than a structuring element.

4.2.8.5 Understanding Dilation and Erosion:

In the morphological dilation and erosion operations, the state of any given pixel in the output image is determined by applying a rule to the corresponding pixel and its neighbors in the input image. The rule used to process the pixels defines the operation as a dilation or an erosion. This table lists the rules for both dilation and erosion.

Rules for Grayscale Dilation and Erosion	
Operation	Rule
Dilation	The value of the output pixel is the <i>maximum</i> value of all the pixels in the input pixel's neighborhood. In a binary image, if any of the pixels is set to the value 1, the output pixel is set to 1.
Erosion	The value of the output pixel is the <i>minimum</i> value of all the pixels in the input pixel's neighborhood. In a binary image, if any of the pixels is set to 0, the output pixel is set to 0.

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TABLE 4.5.3 RULES FOR GREYSCALE DILATION & EROSION

The following figure illustrates the dilation of a binary image. In the figure, note how the structuring element defines the neighborhood of the pixel of interest, which is circled. (See Structuring Elements for more information.) The dilation function applies the appropriate rule to the pixels in the neighborhood and assigns a value to the corresponding pixel in the output image. In the figure, the morphological dilation function sets the value of the output pixel to 1 because one of the elements in the neighborhood defined by the structuring element is on.

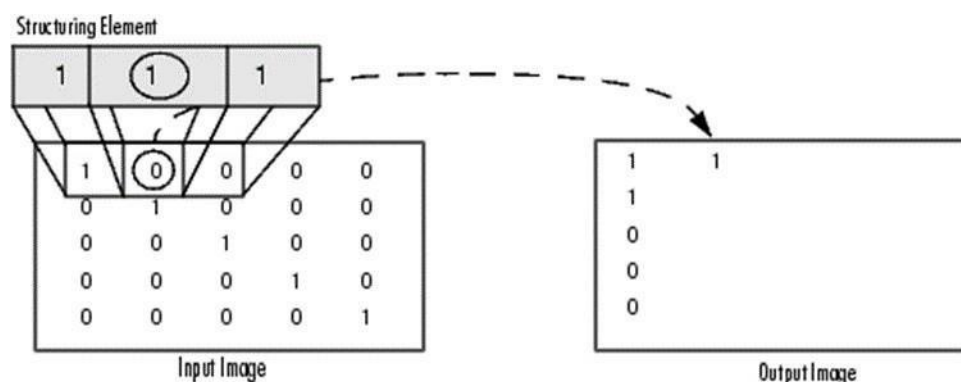


Fig 4.5.1 Morphological Processing of a Binary Image

The following figure illustrates this processing for a grayscale image. The figure shows the processing of a particular pixel in the input image. Note how the function applies the rule to the input pixel's neighborhood and uses the highest value of all the pixels in the neighborhood as the value of the corresponding pixel in the output image.

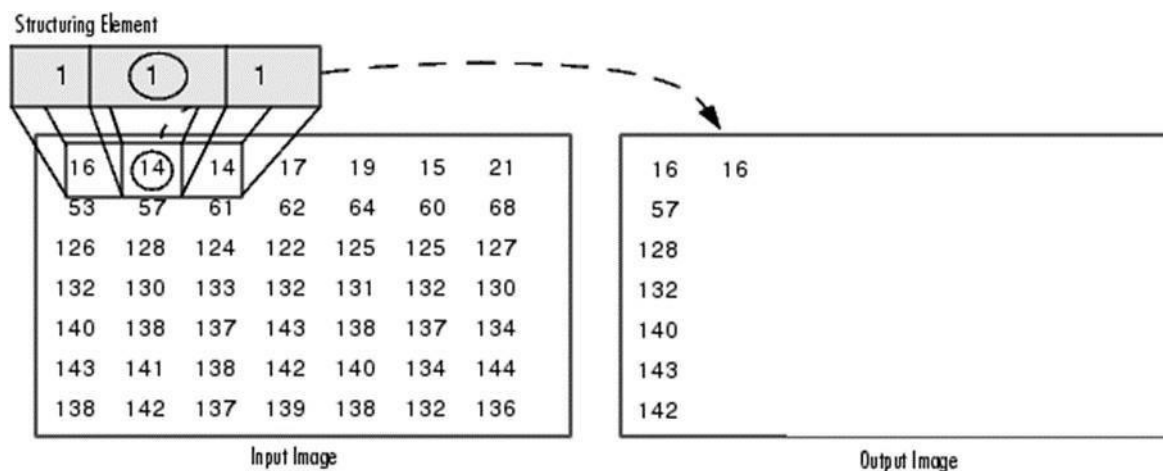


Fig 4.5.2 Morphological Processing of a Gray Image

4.2.8.6 Processing Pixels at Image Borders

Morphological functions position the origin of the structuring element, its center element, over the pixel of interest in the input image. For pixels at the edge of an image, parts of the neighborhood defined by the structuring element can extend past the border of the image.

To process border pixels, the morphological functions assign a value to these undefined pixels, as if the functions had padded the image with additional rows and columns. The value of these "padding" pixels varies for dilation and erosion operations. The following table details the padding rules for dilation and erosion for both binary and grayscale images.

4.2.8.7 Dilating an Image

- To dilate an image, use the imdilate function. The imdilate function accepts two primary arguments:
- The input image to be processed (grayscale, binary, or packed binary image)

- A structuring element object, returned by the `strel` function, or a binary matrix defining the neighborhood of a structuring element
- `imdilate` also accepts two optional arguments: `PADOPT` and `PACKOPT`. The `PADOPT` argument affects the size of the output image. The `PACKOPT` argument identifies the input image as packed binary. (See the `bwpack` reference page for information about binary image packing.)
- To expand all sides of the foreground component, the example uses a 3-by-3 square structuring element object. `SE = strel('square',3)`
- To dilate the image, pass the image, `BW`, and the structuring element, `SE`, to the `imdilate` function. Note how dilation adds a rank of 1's to all sides of the foreground object.

4.2.8.8 Eroding an Image

To erode an image, use the `imerode` function. The `imerode` function accepts two primary arguments:

- The input image to be processed (grayscale, binary, or packed binary image)
 - A structuring element object, returned by the `strel` function, or a binary matrix defining the neighborhood of a structuring element
- `imerode` also accepts three optional arguments: `PADOPT`, `PACKOPT`, and `M`. The `PADOPT` argument affects the size of the output image. The `PACKOPT` argument identifies the input image as packed binary. If the image is packed binary, `M` identifies the number of rows in the original image.

The following example erodes the binary image, `circbw.tif`:

- Read the image into the MATLAB workspace.
- Create a structuring element. The following code creates a diagonal structuring element object. (For more information about using the `strel` function.
- Call the `imerode` function, passing the image, `BW`, and the structuring element, `SE`, as arguments.
- Notice the diagonal streaks on the right side of the output image. These are due to the shape of the structuring element.

4.2.8.9 Combining Dilation and Erosion

Dilation and erosion are often used in combination to implement image processing operations. For example, the definition of a morphological opening of an image is an erosion followed by a dilation, using the same structuring element for both operations. The related operation, morphological closing of an image is the reverse: it consists of dilation followed by an erosion with the same structuring element.

The following section uses `imdilate` and `imerode` to illustrate how to implement a morphological opening. Note, however, that the toolbox already includes the `imopen` function which performs this processing. The toolbox includes functions that perform many common morphological operations.

4.3. HARDWARE USED:

HDD:>90GB

PROCESSOR: >Pentium IV 2.4GHz

SYSTEM TYPE: 32bit RAM:8GB

OS: WINDOWS10

4.4 SOFTWARE USED:

Tool : Matlab R2018a

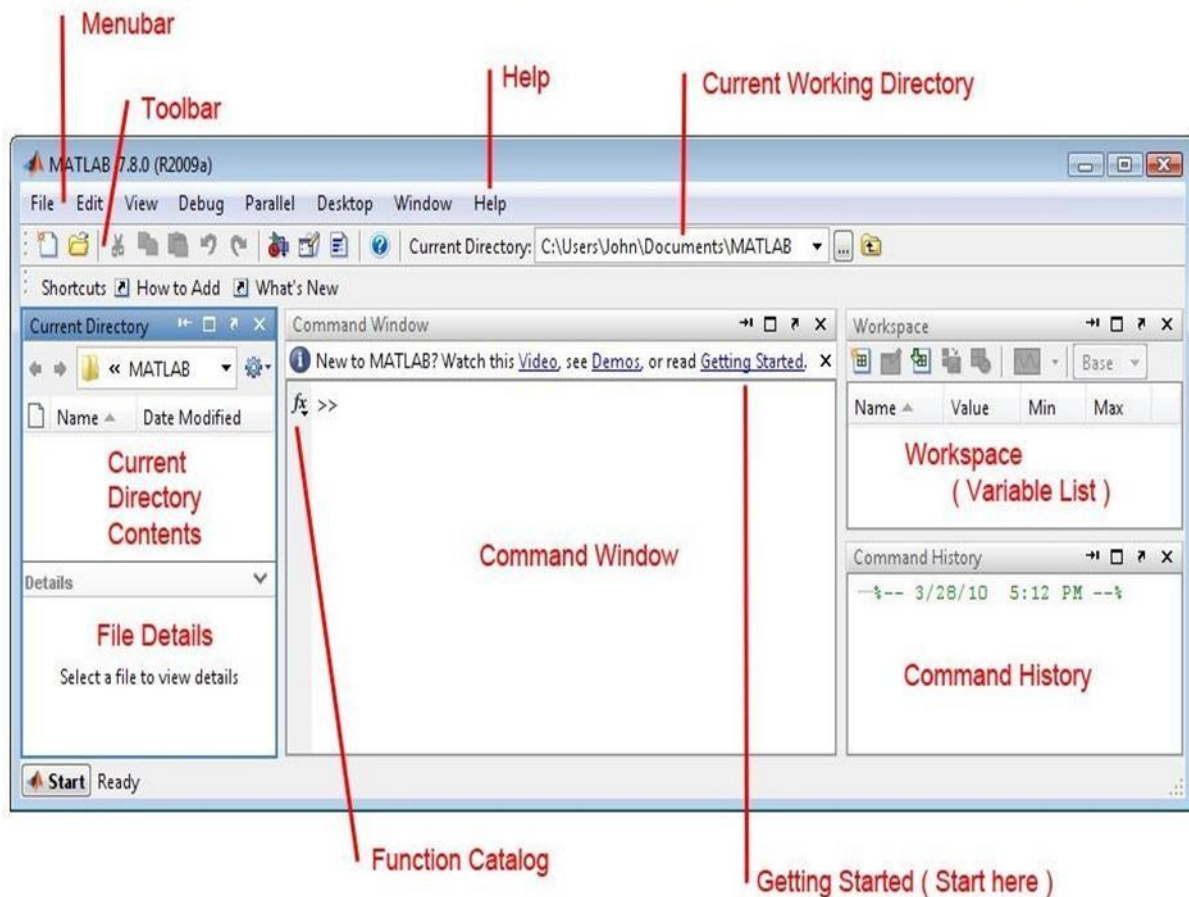
Tool Box: Image Processing

4.4.1 MATLAB:

MATLAB is a programming language developed by MathWorks. It started out as a matrix programming language where linear algebra programming was simple. It can be run both under interactive sessions and as a batch job. MATLAB(matrix laboratory) is a fourth generation high-level programming language and interactive environment for numerical computation, visualization and programming. MATLAB is developed by MathWorks. It allows matrix manipulations; plotting of functions and data; implementation of algorithms; creation of user interfaces; interfacing with programs

written in other languages, including C, C++, Java, and FORTRAN; analyze data; develop algorithms; and create models and applications. It has numerous built in commands and math functions that help you in mathematical calculations, generating plots and performing numerical methods.

The MATLAB Work Environment



4.8 MATLAB WINDOW

4.4.2 The MATLAB System

The MATLAB system consists of five main parts:

- MATLAB Language
- MATLAB Working environment
- Handle graphics
- MATLAB Mathematical function library
- MATLAB Application Program Interface

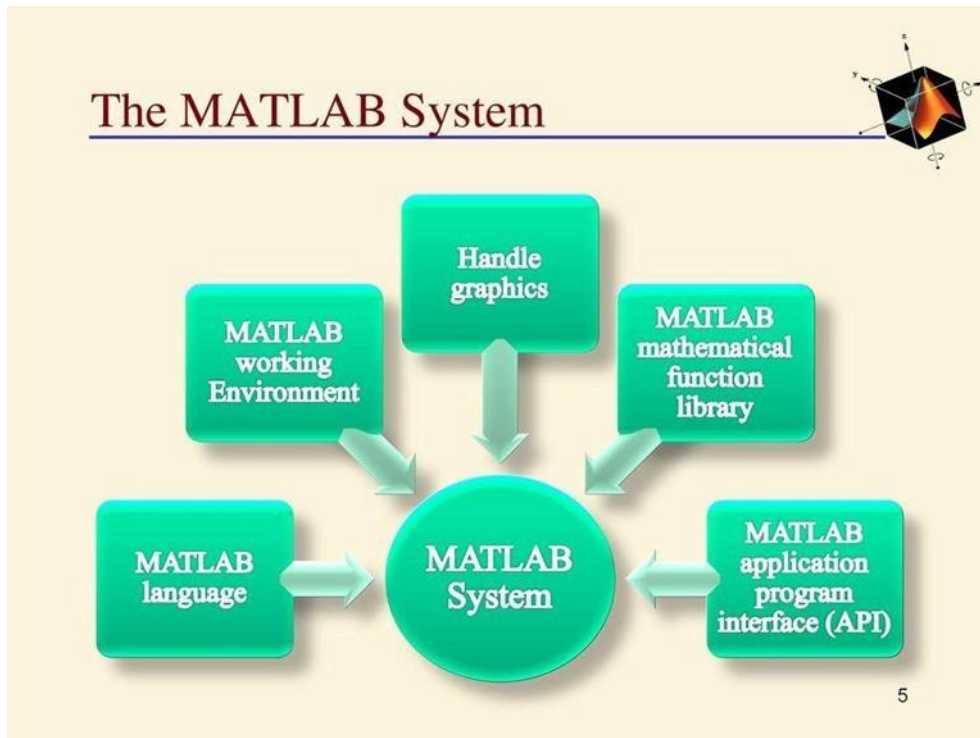


FIG 4.8.1 MATLAB SYSTEM

The MATLAB language.

This is a high-level matrix/array language with control flow statements, functions, data structures, input/output, and object-oriented programming features. It allows both "programming in the small" to rapidly create quick and dirty throw-away programs, and "programming in the large" to create complete large and complex application programs.

The MATLAB working environment.

This is the set of tools and facilities that you work with as the MATLAB user or programmer. It includes facilities for managing the variables in your workspace and importing and exporting data. It also includes tools for developing, managing, debugging, and profiling M-files, MATLAB's applications

Handle Graphics.

This is the MATLAB graphics system. It includes high-level commands for two-dimensional and three-dimensional data visualization, image processing, animation, and presentation graphics. It also includes low-level commands that allow you to fully customize the appearance of graphics as well as to build complete Graphical User Interfaces on your MATLAB applications.

The MATLAB mathematical function library.

This is a vast collection of computational algorithms ranging from elementary functions like sum, sine, cosine, and complex arithmetic, to more sophisticated functions like matrix inverse, matrix eigenvalues, Bessel functions, and fast Fourier transforms.

MATLAB Application Program Interface.

The MATLAB Data API provides a way for applications running outside of MATLAB to work with MATLAB data through a MATLAB-neutral interface. The API uses modern C++ semantics and design patterns and avoids data copies whenever possible by using MATLAB copy-on-write semantics.

4.4.3 MATLAB'S POWER OF COMPUTATIONAL MATHEMATICS:

MATLAB is used in every facet of computational mathematics. Following are some commonly used mathematical calculations where it is used most commonly:

- Dealing with Matrices and Arrays
- Plotting and graphics
- Linear Algebra Algebraic Equations Non-linear Function
- Statistics Data Analysis
- Calculus and Differential Equations Numerical Calculations
- Integration Transforms Curve Fitting

4.4.4 FEATURES OF MATLAB:

It is a high-level language for numerical computation, visualization and application development. It also provides an interactive environment for iterative exploration, design and problem solving. It provides vast library of mathematical functions for linear algebra, statistics, Fourier analysis, filtering, optimization, numerical integration and solving ordinary differential equations. It provides built-in graphics for visualizing data and tools for creating custom plots. MATLAB's programming interface gives development tools for improving codequality, maintainability and maximizing performance. It provides tools for building applications with custom graphical interfaces. It provides functions for integrating MATLAB based algorithms with external applications and languages such as C, Java, .NET and Microsoft Excel.

4.4.5 Development Tools

MATLAB includes a variety of tools for efficient algorithm development, including:

- **Command Window** – Lets you interactively enter data, execute commands and programs, and display results
- **MATLAB Editor** – Provides editing and debugging features, such as setting break points and stepping through individual lines of code
- **Code Analyzer** – Automatically checks code for problems and recommends modifications to maximize performance and maintainability
- MATLAB Profiler** – Measures performance of MATLAB programs and identifies areas of code to modify for improvement

Workflow for MATLAB Toolboxes

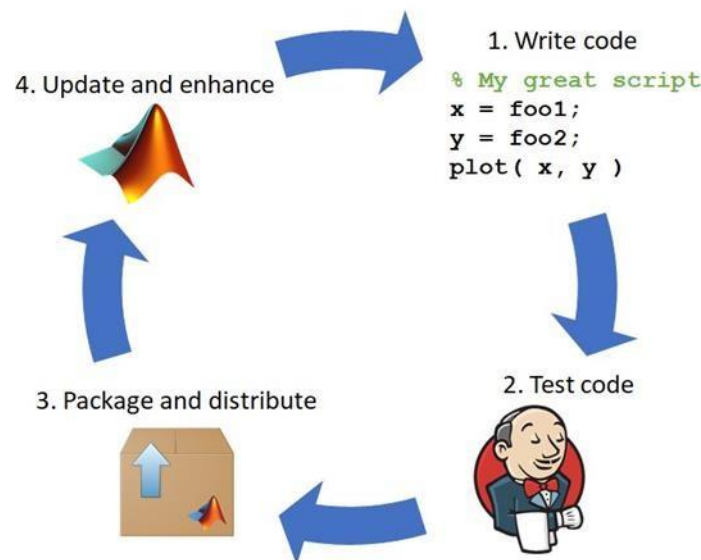


FIG 4.8.4 MATLAB TOOL

4.4.6 USES OF MATLAB:

MATLAB is widely used as a computational tool in science and engineering encompassing the fields of physics, chemistry, math and all engineering streams.

It is used in a range of applications including:

- signal processing and Communications
- image and video Processing
- control systems
- test and measurement
- computational finance
- computational biology

4.5. METHODOLOGY:

- Image acquisition is taking an input image ,which is for processing and its called input image.
- Color conversion is the part of preprocessing and enhancement consist of filtering ,histogram and adaptive histogram.
- Texture feature calculations use the contents of the GLCM to give a measure of the variation in intensity (image texture) at the pixel of interest.
- Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. A morphological operation on a binary image creates a new binary image in which the pixel has a non- zero value only if the test is successful at that location in the input image.
- The proposed method presents an algorithm called the skin locus algorithm used to predict and classify the diabetic retinopathy in order to detect the disease earlier and cure it completely.

CHAPTER 5

RESULTS AND DISCUSSION

RESULT:

We proposed an automatic detection of diabetic retinopathy in retinal images, the result obtained from the diagnosis of DR has been shown in the Figure. One hundred ten images (normal images and abnormal images) have been taken from DIABETDB1 database. Out of these, sixty one eye images are used as training sample with fivefold validation and fifty two images as testing sample. There are six testing samples shown in the result which accurately classify using linear SVM classifier. Simulation has been performed in MATLAB R2018a. Accuracy of proposed DR detection system are evaluated based on sensitivity and specificity.

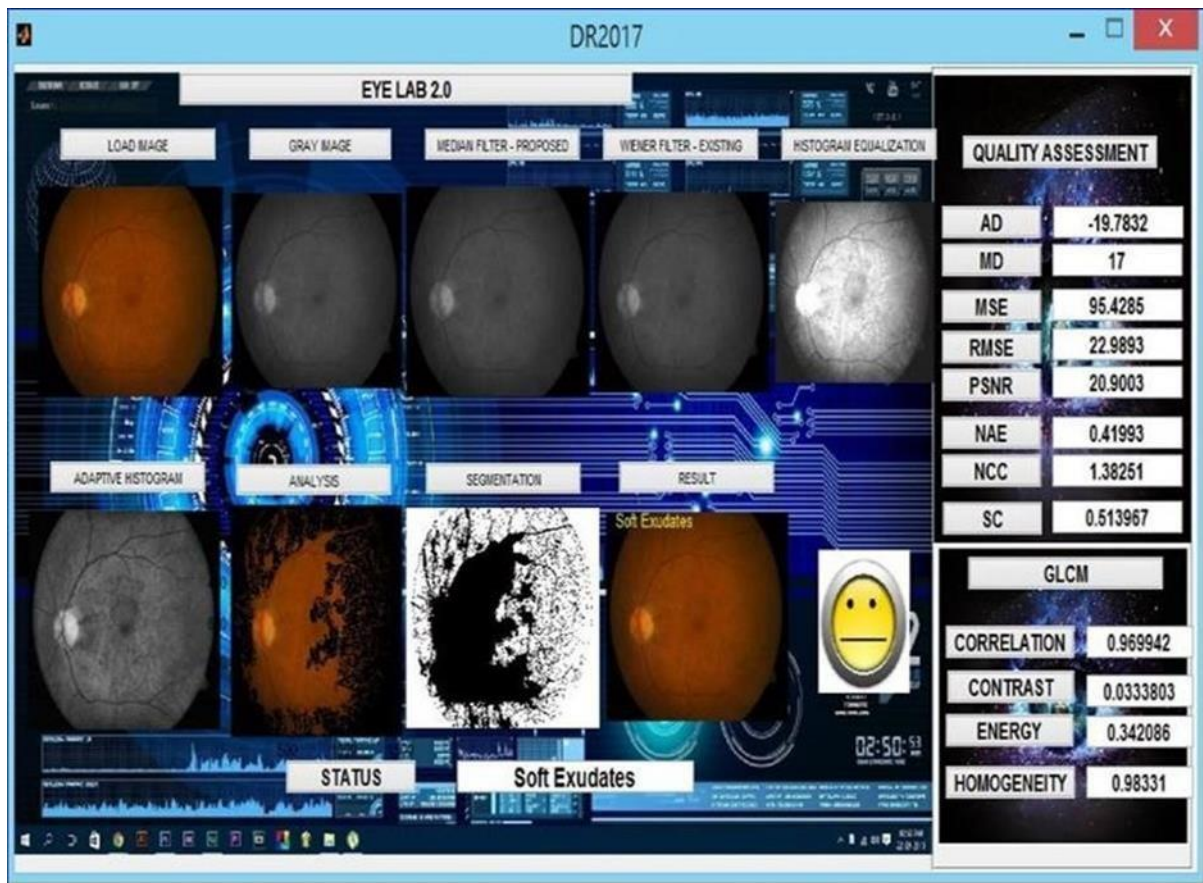


FIG 5.1 RUN PROGRAM

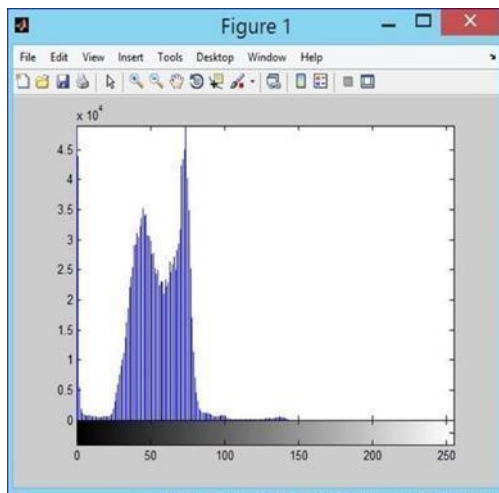


FIG 5.2 GRAY LEVEL IMAGE

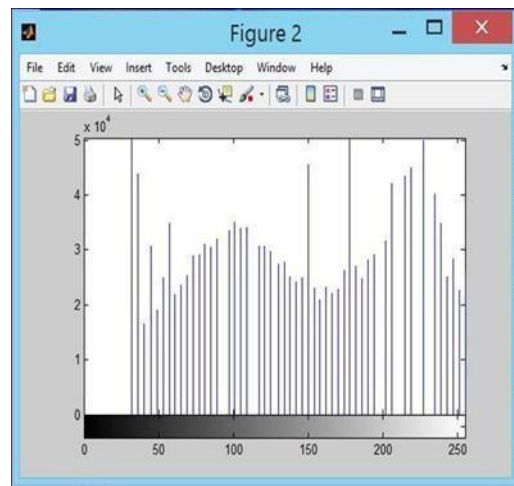


FIG 5.3 HISTOGRAM EQUALIZATION

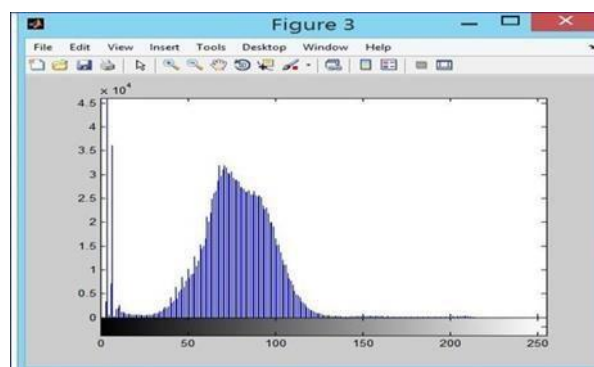


FIG 5.4 ADAPTIVE HISTOGRAM



FIG 5.5 RESULT

NORMAL EYE:

The eye can be easily understood if you think of it as a camera. The eye is working in almost the same way. The lens is transparent in a healthy eye and allows light to pass through. Light is focused around the cornea and the lens on a thin layer of tissue called the retina. The retina is working like a film in a frame.

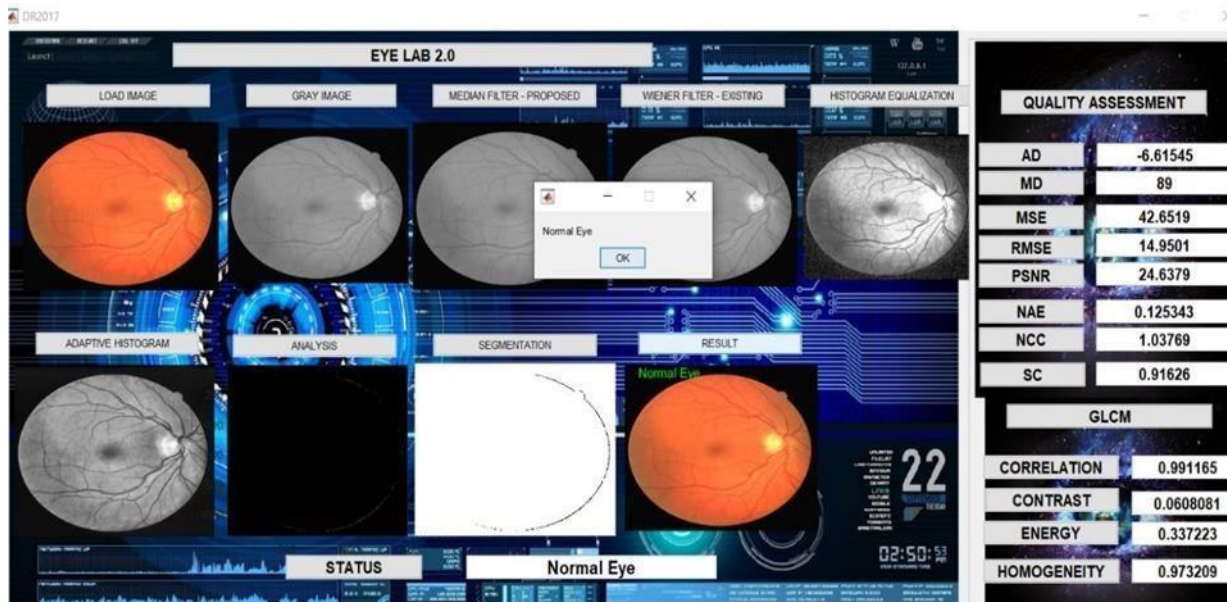


FIG 5.6 NORMAL EYE

LOAD IMAGES NO.	QUALITY ASSESSMENT								GLCM			
	AD	MD	MSE	RMSE	PSNR	NAE	NCC	SC	CORRELATION	CONTRAST	ENERGY	HOMOGENEITY
006	-17.739	52	74.186	22.918	20.927	0.2825	1.245	0.6321	0.97	0.04	0.28	0.97
010	-6.6154	89	42.651	14.950	24.637	0.12534	1.0376	0.9162	0.99	0.06	0.33	0.97
012	-16.789	26	81.610	20.096	22.068	0.2869	1.2530	0.62783	0.97	0.03	0.28	0.98
020	-18.320	37	68.605	23.238	20.806	0.27019	1.2318	0.6469	0.97	0.05	0.24	0.97
021	-17.244	43	73.910	21.380	21.530	0.2797	1.2372	0.6426	0.98	0.04	0.22	0.97
026	-20.865	11	108.01	24.209	20.451	0.5967	1.5470	0.408	0.9	0.04	0.43	0.97
027	-6.2609	98	42.185	16.714	23.668	0.1407	1.0321	0.9206	0.99	0.06	0.26	0.96
029	-20.909	42	86.407	27.126	19.463	0.389	1.372	0.5185	0.96	0.04	0.29	0.97
039	-7.543	80	47.472	15.248	24.466	0.1342	1.0513	0.891865	0.9	0.06	0.32	0.97
043	-16.50	41	62.257	21.459	21.459	0.2266	1.1914	0.6939	0.98	0.05	0.26	0.97
056	-17.402	65	73.591	23.229	20.810	0.30166	1.2256	0.6469	0.98	0.05	0.22	0.97
057	-11.476	58	60.354	16.029	24.032	0.1728	1.1115	0.7984	0.98	0.06	0.39	0.97

TABLE 5.1 NORMAL EYE

Often a bright red patch, called a subconjunctival haemorrhage, occurs on the white of the eye. This also occurs after straining or coughing, which creates a broken blood vessel on the surface of the eye. Much of the time, there is no pain and the vision is normal.

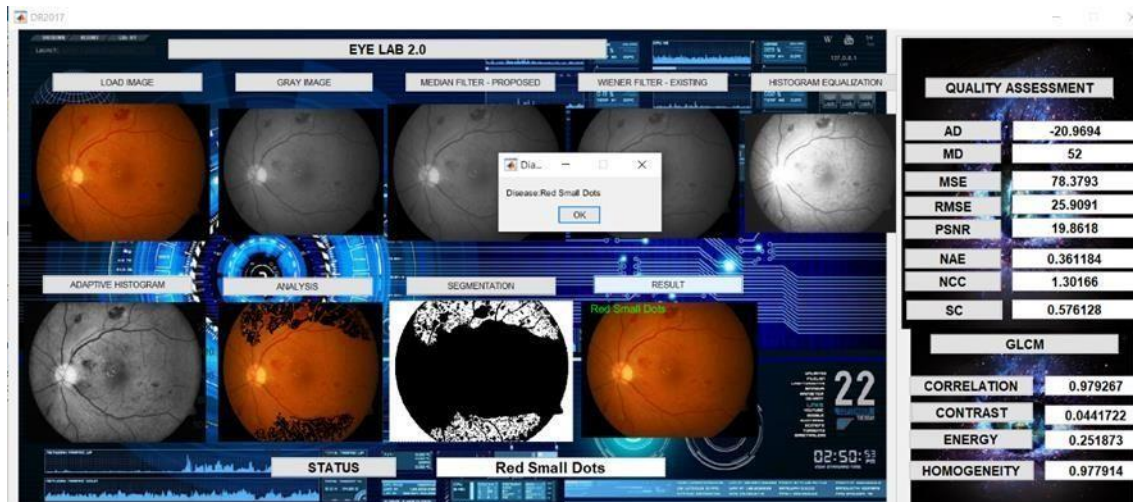


FIG 5.7 RED SMALL DOTS

LO AD IM AG ES	QUALITY ASSESSMENT								GLCM			
	AD	M D	MS E	RMS E	PSN R	NAE	NCC	SC	CORR ELATI ON	CONT RAST	ENE RGY	HO MO GEN I TY
003	- 18.5 084	45	91. 769	21.6 927	21.4 045	0.379 634	1.33 186	0.553 122	0.968 451	0.0407 786	0.33 2002	0.9 769 11
008	- 20.9 694	52	78. 379 3	25.9 091	19.8 618	0.361 184	1.30 166	0.576 128	0.979 267	0.0441 722	0.25 1873	0.9 779 14
017	- 14.4 231	49	78. 736	18.4 756	22.7 988	0.240 465	1.20 662	0.676 284	0.973 963	0.0492 296	0.27 4954	0.9 753 85
019	- 17.7 802	56	70. 447 8	24.2 9	20.4 223	0.284 085	1.23 395	0.641 085	0.981 637	0.0440 684	0.24 6439	0.9 779 66
022	- 19.2 596	21	90. 960 2	23.1 366	20.8 448	0.369 258	1.34 636	0.542 01	0.963 483	0.0409 675	0.33 5361	0.9 795 16
030	- 20.3 295	22	84. 721 9	24.4 518	20.3 646	0.370 286	1.32 612	0.556 103	0.974 475	0.0404 939	0.29 0449	0.9 797 53
033	- 21.6 789	38	79. 773 8	25.9 626	19.8 439	0.364 483	1.32 458	0.559 11	0.964 22	0.0657 542	0.25 0949	0.9 671 23
034	- 20.8 203	38	84. 290 7	25.0 115	20.1 68	0.376 54	1.33 165	0.551 951	0.967 613	0.0485 409	0.29 6118	0.9 757 31
049	- 19.6 232	49	89. 799 5	23.8 492	20.5 813	0.426 683	1.29 496	0.574 327	0.982 6	0.0441 397	0.26 8938	0.9 779 31
054	- 20.1 167	43	82. 318 2	24.6 902	20.2 803	0.363 098	1.31 093	0.569 347	0.978 455	0.0419 699	0.26 5847	0.9 790 17
060	- 21.2 087	16	101 .27	24.6 132	20.3 075	0.492 06	1.47 16	0.454 425	0.923 759	0.0497 02	0.47 2539	0.9 751 51
061	- 21.7 215	46	93. 344 3	25.7 96	19.8 998	0.485 925	1.40 345	0.495 245	0.976 178	0.0453 322	0.28 3194	0.9 773 74

TABLE 5.2 RED SMALL DOTS

HEMORRHAGES:

Eye bleeding usually involves bleeding or a broken blood vessel below the outer surface of the eye. The whole white part of your eye may look red or blood, or you may have spots or red areas in your eye. Another less common type of bleeding, or bleeding, may happen in the middle, coloured part of your eye.



FIG 5.8 HEMORRHAGES

LOAD IMAGES	QUALITY ASSESSMENT								GLCM			
	AD	MD	MSE	RMSE	PSNR	NAE	NCC	SC	CORRELATION	CONTRAST	ENERGY	HOMOGENEITY
009	-	39	101.544	23.1415	20.843	0.48855	1.447	0.468	0.961	0.040	0.353	0.979
014	-	24	89.1781	25.5287	19.9902	0.4065	1.36861	0.5217	0.973	0.034	0.324	0.982
016	-	23	94.1425	21.0248	21.6762	0.334701	1.31965	0.5641	0.956	0.047	0.330	0.976
024	-	15	92.9819	20.1073	22.0637	0.333	1.31722	0.5692	0.975	0.025	0.353	0.987
038	-20.224	12	115.741	23.7288	20.6253	0.744896	1.67269	0.348866	0.944	0.0305	0.471	0.984
040	-	30	103.47	25.4009	20.0338	0.554291	1.51534	0.427376	0.949	0.049	0.36	0.975
041	-	30	103.473	25.4009	20.0338	0.5542	1.51534	0.4272	0.949	0.049	0.360	0.975
042	-	14	118.081	24.478	20.3553	0.7936	1.7258	0.327688	0.942	0.038	0.501	0.980
044	-	12	102.25	22.6293	21.0374	0.4602	1.444	0.47267	0.928	0.050	0.442	0.974
046	-	11	112.395	22.0766	21.2522	0.596621	1.57017	0.399885	0.906	0.0519	0.449	0.974
048	-	41	95.7237	23.8288	20.5888	0.459681	1.39263	0.505	0.956	0.062	0.32	0.968
051	-	19	102.156	26.227	19.7558	0.5486	1.5119	0.4283	0.931	0.059	0.368	0.970
059	-	21	90.5082	21.7911	21.3652	0.3737	1.3186	0.56277	0.969	0.044	0.297	0.977

TABLE 5.3 HEMORRHAGES

HARD EXUDATES:

Hard exudates are thin white or yellowish-white deposits with sharp margins. They also look waxy, glossy, or glistening. They are found in the outer layers of the retina, deep into the retinal vessels. Microaneurysms that appear as white dots with no visible blood in the lumen are known to be hard exudates.

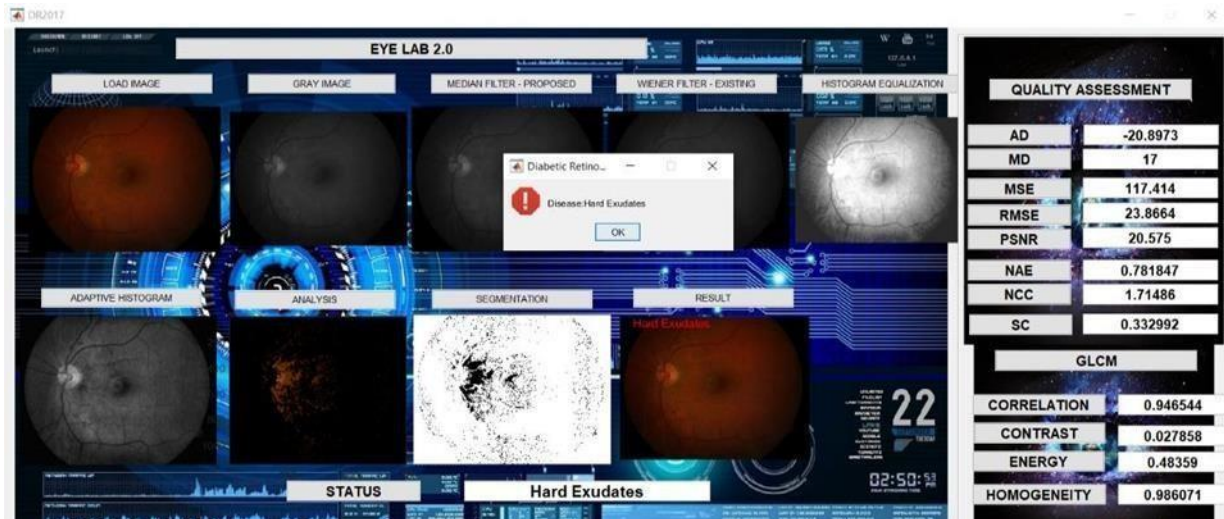


FIG 5.9 HARD EXUDATES

LOAD D IMA GES NO.	QUALITY ASSESSMENT								GLCM			
	AD	M D	MS E	RM SE	PS NR	NAE	NC C	SC	CORREL ATION	CON TRAST	ENE RGY	HOMOG ENEITY
023	- 16. 802	1 0	108 .65	19. 207	22. 461	0.48 868	1.4 344	0.47 7	0.95	0.03	0.39	0.98
032	- 20. 897	1 7	117 .41	23. 866	20. 575	0.78 184	1.7 148	0.33 299	0.94	0.02	0.4	0.98
037	- 21. 010	1 0	112 .65	23. 833	20. 587	0.69 885	1.6 025	0.37 895	0.93	0.04	0.43	0.97
045	- 19. 495	7	118 .25	22. 313	21. 159	0.74 90	1.6 854	0.34 38	0.93	0.03	0.48	0.98

TABLE 5.4 HARD EXUDATES

SOFT EXUDATES:

Cotton wool spots are an unusual finding on a fundusoscopic examination of the eye's retina. They appear on the retina as fuzzy white patches. Damage to nerve fibres results in accumulations of axoplasmic material within the nerve fibre layer, which triggers them.

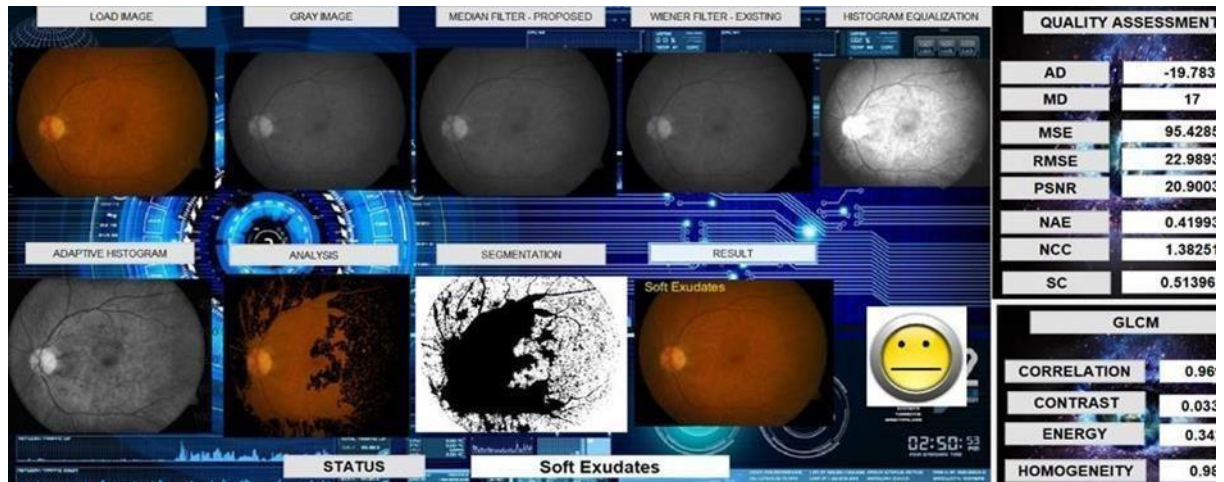


FIG 5.10 SOFT EXUDATES

LOAD IMAGES	QUALITY ASSESSMENT								GLCM			
	AD	MD	MSE	RMSE	PSNR	NAE	NCC	SC	CORRELATION	CONTRAST	ENERGY	HOMOGENEITY
001	-20.6327	28	89.6739	24.058	20.5056	0.399514	1.35536	0.533986	0.9750	0.0311	0.3274	0.9844
002	-19.7832	17	85.4285	22.9893	20.9003	0.41993	1.38251	0.513967	0.9699	0.0333	0.3420	0.9833
004	-19.0707	19	98.3365	22.2430	21.17893	0.433893	1.38706	0.50813	0.9621	0.0380	0.346913	0.980
005	-15.0657	54	67.3629	21.0076	21.6833	0.227769	1.19005	0.6935930	0.9831	0.03992	0.2926	0.9800
007	-22.4729	38	108.605	26.301	19.731	0.6668	1.5992	0.3822	0.9489	0.0469	0.3912	0.9765
011	-21.485	27	93.121	25.580	19.972	0.4315	1.4090	0.4951	0.9596	0.044	0.3326	0.9779
013	-20.8089	26	94.5466	24.381	20.389	0.4468	1.4036	0.4977	0.9692	0.0352	0.3263	0.9823
018	-20.765	31	94.773	24.5964	20.3134	0.445553	1.39785	0.400512	0.9661	0.040	0.3256	0.9823
025	-18.3835	26	90.7569	20.0772	21.2519	0.354185	1.33309	0.554518	0.9695	0.0355	0.3312	0.9822
028	-21.364	38	25.2156	25.2156	20.097	0.5048	1.4689	0.4555	0.9514	0.0485	0.3762	0.9757
031	-20.543	38	97.094	24.5132	20.342	0.466974	1.42866	0.481498	0.9526	0.05277	0.3522	0.9736
035	-22.846	18	96.864	26.6776	19.6079	0.5002	1.4582	0.4599	0.9587	0.045	0.3248	0.9770
036	-21.119	30	93.884	24.508	20.3444	0.4483	1.4038	0.498685	0.9704	0.037	0.3155	0.9814
047	-20.6129	33	93.4278	25.8714	19.8744	0.444687	1.3156	0.553	0.9761	0.0674	0.306	0.9663
050	-21.2603	35	82.4968	26.0715	19.8075	0.37191	1.33598	0.548498	0.9721	0.0428	0.2980	0.9785

TABLE 5.5 SOFT EXUDATES

DISCUSSION:

Z. A. Omar et al.[3] (2017) proposed a calculation that comprises of DR identification technique with the plan to improve the exactness of the current frameworks. The strategies used to distinguish DR highlights, to be specific exudates, hemorrhages and veins can be ordered into a few stages which are picture pre preparing, vessel and hemorrhages identification, optic plate evacuation and exudate discovery. Shailesh Kumar[2] and Basant Kumar (2018) presents an improved diabetic retinopathy identification conspire by extricating exact zone and number of microaneurysm from shading fundus pictures by SVM. we obtained the result from the diagnosis of DR. we took 110 images (normal and abnormal) from DIABETDB1 database. out of these 58 eye images are used as training sample with five fold validation and 52 images as testing sample. there are 6 testing sample shown in the result which accurately classify using linear SVM classifier. Simulation has been performed in MATLAB R2018a. accuracy of proposed DR detection system are evaluated based on sensitivity and specificity.

FORMULA:

- %Average Difference
 $AD = \text{sum}(\text{sum}(\text{error})) / (M * N);$
- %Maximum Difference
 $MD = \text{max}(\text{max}(\text{error}));$
- %Mean Square Error
 $MSE = \text{sum}(\text{sum}(\text{error}.*\text{error})) / (M * N);$
- %Root Mean Square Error
 $RMSE = \text{sqrt}(MSE);$
- %Peak Signal to Noise Ratio
 $PSNR = 10 * \log(255*255/MSE) / \log(10);$
- Normalized Absolute Error
 $NAE = \text{sum}(\text{sum}(\text{abs}(\text{error}))) / \text{sum}(\text{sum}(\text{origImg}));$
- %Normalized Cross Correlation
 $NK = \text{sum}(\text{sum}(\text{origImg} .* \text{distImg})) / \text{sum}(\text{sum}(\text{origImg} .* \text{origImg}));$
- Structural Content
 $SC = \text{sum}(\text{sum}(\text{origImg}.*\text{origImg}))/\text{sum}(\text{sum}(\text{distImg}.*\text{distImg}));$

CHAPTER 6

SUMMARY AND CONCLUSION

SUMMARY:

In this project we developed an automatic detector of retinopathy. The data is gathered in this process in order to analyses. We obtained the diagnosis of DR from DIABETDB1 database and the data are stored . For finding defects and classification of exudates in the coloured retinal image. Several image processing techniques including Image Enhancement, Segmentation, Classification, and registration has been developed for the early detection of DR on the basis of features such as blood vessels, exudes, hemorrhages and micro aneurysms. Image Processing techniques are evaluated on the basis of their results. Exudates are found using their high gray level variation, and the classification of exudates is done with exudates features and SVM classifier.

CONCLUSION:

In this paper we proposed a picture information framework was projected for assessing and examination techniques for automatic recognition of diabetic retinopathy. It provides AN integrated system to benchmarking the methods, it additionally indicate apparent deficiencies within the tissue layer. it's determined that study of retinal footage is that the key contribution to tell apart DR Since its early discovery is feasible it helps to treat consequently and therefore the vision loss is avoided.

CHAPTER 7

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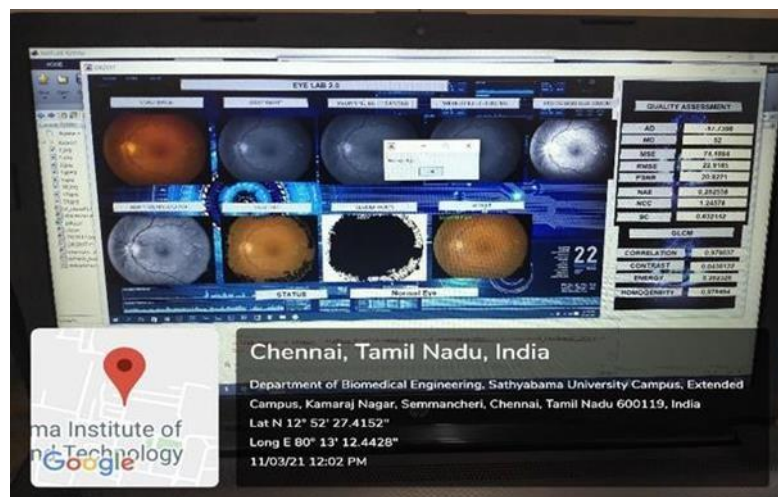
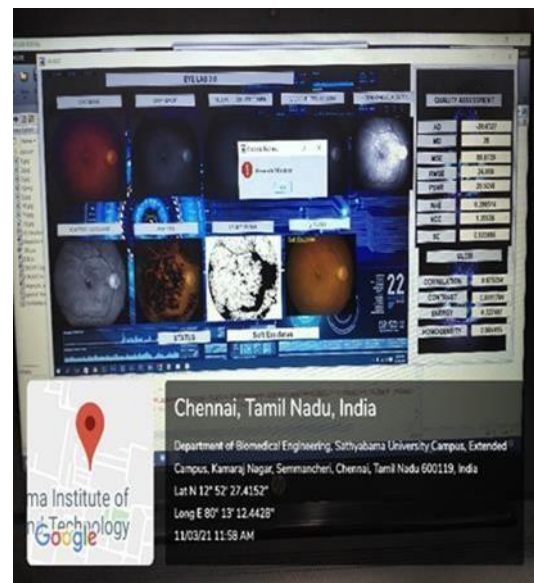
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GEO TAGGING



APPENDIX:

```
function varargout = DR2017(varargin)

% DR2017 MATLAB code for DR2017.fig

%   DR2017, by itself, creates a new DR2017 or raises the existing
%   singleton*.

%
%   H = DR2017 returns the handle to a new DR2017 or the handle to
%   the existing singleton*.

%
%   DR2017('CALLBACK',hObject,eventData,handles,...) calls the local
%   function named CALLBACK in DR2017.M with the given input arguments.
%
%   DR2017('Property','Value',...) creates a new DR2017 or raises the
%   existing singleton*. Starting from the left, property value pairs are
%   applied to the GUI before DR2017_OpeningFcn gets called. An
%   unrecognized property name or invalid value makes property application
%   stop. All inputs are passed to DR2017_OpeningFcn via varargin.
%
%   *See GUI Options on GUIDE's Tools menu. Choose "GUI allows only one
%   instance to run (singleton)".
%
% See also: GUIDE, GUIDATA, GUIHANDLES

% Edit the above text to modify the response to help DR2017
```

```
% Last Modified by GUIDE v2.5 15-Mar-2018 19:40:01
```

```
% Begin initialization code - DO NOT EDIT
```

```
gui_Singleton = 1;
```

```
gui_State = struct('gui_Name',      mfilename, ...  
    'gui_Singleton', gui_Singleton, ...  
    'gui_OpeningFcn', @DR2017_OpeningFcn, ...  
    'gui_OutputFcn', @DR2017_OutputFcn, ...  
    'gui_LayoutFcn', [] , ...  
    'gui_Callback', []);
```

```
if nargin && ischar(varargin{1})
```

```
    gui_State.gui_Callback = str2func(varargin{1});
```

```
end
```

```
if narginout
```

```
    [varargout{1:narginout}] = gui_mainfcn(gui_State, varargin{:});
```

```
else
```

```
    gui_mainfcn(gui_State, varargin{:});
```

```
end
```

```
% End initialization code - DO NOT EDIT
```

```
% --- Executes just before DR2017 is made visible.
```

```
function DR2017_OpeningFcn(hObject, eventdata, handles, varargin)
```

```
% This function has no output args, see OutputFcn.
```

```
% hObject    handle to figure
```

```
% eventdata reserved - to be defined in a future version of MATLAB
```

```
% handles    structure with handles and user data (see GUIDATA)
```

```
% varargin   command line arguments to DR2017 (see VARARGIN)
```

```
% Choose default command line output for DR2017
```

```
handles.output = hObject;
```

```
% Update handles structure
```

```
guidata(hObject, handles);
```

```
% UIWAIT makes DR2017 wait for user response (see UIRESUME)
```

```
% uiwait(handles.figure1);
```

```
% --- Outputs from this function are returned to the command line.
```

```
function varargout = DR2017_OutputFcn(hObject, eventdata, handles)
```

```
% varargout cell array for returning output args (see VARARGOUT);
```

```
% hObject    handle to figure
```

```
% eventdata reserved - to be defined in a future version of MATLAB
```

```
% handles    structure with handles and user data (see GUIDATA)
```

```
% Get default command line output from handles structure
```

```
varargout{1} = handles.output;
```

```
set(handles.edit1,'String',' ');
```

```
set(handles.edit2,'String',' ');
```

```
set(handles.edit3,'String',' ');
```

```
set(handles.edit4,'String',' ');
```

```
set(handles.edit5,'String',' ');
```

```
set(handles.edit6,'String',' ');
```

```
set(handles.edit7,'String',' ');
```

```
set(handles.edit8,'String',' ');
```

```
set(handles.edit9,'String',' ');
```

```
set(handles.edit10,'String',' ');
```

```
set(handles.edit11,'String',' ');
```

```
set(handles.edit12,'String',' ');
```

```
set(handles.edit14,'String',' ');
```

```
global a b c;
```

```
a=imread('4.jpeg');
```

```
a=imresize(a,[800 1400]);
```

```
axes(handles.axes1);
```

```
imshow(a);
```

```
b=imread('1.jpg');
```

```
b=imresize(b,[1200 1000]);
```

```
axes(handles.axes12);
```

