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DIABETIC RETINOPATHY DETECTION BY EXTRACTING AREA AND NUMBER OF MICROANEURYSM FROM COLOUR FUNDUS IMAGE

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ABSTRACT Diabetic retinopathy (DR) is an intricacy of diabetes and a main source of vision misfortune. For Diabetic Retinopathy discovery, low quality of retinal pictures makes more troublesome the examination for ophthalmologist. Automatic segmentation of blood vessels in retina is helpful for ophthalmologists to screen larger populations. This project presents a new automatic analysis to extract blood vessels with high accuracy. This project presents an improved diabetic retinopathy detection scheme by extracting accurate area and ate number of microaneurysm from color fundus images. Regular screening of eye is crucial for detection and dealing with diabetic retinopathy. Diabetic retinopathy (DR) is an eye disease which occurs due to damage of retina as a result of long illness of diabetic mellitus. Microaneurysms (MA) are tiny red spots on retina, shaped by inflating out of fragile part of the blood vessels. The recognition of MA at primary stage is very crucial and it is the first step in inhibiting DR. A variety of methods have been proposed for detection and diagnosis of DR. In this paper, there are two features namely; number and area of MA have been determined. Initially, pre-processing techniques like green channel extraction, histogram equalization and morphological process have been used. For detection of microaneurysms, principal component analysis (PCA), contrast limited adaptive histogram equalization (CLAHE), morphological process, averaging filtering have been used. Classification of DR has been done by linear Support vector machine (SVM).

Keywords: principal component analysis, contrast limited adaptive histogram equalization, linear Support vector machine, Microaneurysms, Diabetic retinopathy.

INTRODUCTION This chapter gives an overview of extension in Enhanced Detection Of Diabetic Retinopathy Using Advanced Filters which was intimated in the below data. It crucially comprises of optimized Gabor filter with entropy threshold. Diabetic Retinopathy (DR) is the result of damage due to diabetes to the very small blood vessels which are located in the retina. The blood vessels which are affected from diabetic retinopathy leads to vision loss. Diabetic retinopathy is a leading reason of adult blindness, and screening can decrease the incidence. Screening just increases the chances that a condition will be neglected, found early, or are able to be cured. It is widely suggested that all persons with diabetes should regularly check for diabetic retinopathy. Computer aided analysis for automatic segmentation of blood vessels in retinal images will help ophthalmologists to screen larger patient database for vessel abnormalities. So many varieties of paths have been suggested for retina blood vessels segmentation. Many image processing methods proposed for retinal vessels extraction. This work is based on "ENHANCED DETECTION OF DIABETIC RETINOPATHY USING ADVANCED FILTERS". Gabor filters[1]have been widely applied to image processing and computer vision application problems such as face recognition and texture segmentation. Gabor filter methods often give false positive detections and fail to detect vessel of different widths and also detection process is much more complicated when retinal image abnormal condition. This paper has been proposed a much robust and fast method of retinal blood. Gabor filter methods often give false positive detections and fail to detect vessel of different widths and also detection process is much more complicated when retinal image abnormal condition. This paper has been proposed a much robust and fast method of retinal blood vessels extraction using optimized Gabor filter with local entropy threshold. Diabetic Retinopathy (DR) is caused by complications of diabetes mellitus which can eventually lead to blindness especially in its advanced stage. Diabetic Retinopathy is the common cause of visual impairment among persons of working age in the developed world. It is predominantly a micro angioplasty in which small blood vessels are particularly Vulnerable to damage from hyperglycemia. Direct hyperglycemic effects on retinal cells are also likely to play a role. It progresses from mild, moderate and severe Non-Proliferative Diabetic Retinopathy (NPDR) to Proliferative Diabetic Retinopathy (PDR).

LITERATURE SURVEY: This chapter gives literature survey of various base papers taken into account before designing this project. It is to outline the importance of each paper and the different roles they have played in the advancement of our own work. [1]. Automated Segmentation of Retinal Blood Vessels using Optimized Gabor Filter with Local Entropy Thresholding by saumitra Kumar kuri, in IJCA, vol-114, no-11, in March 2015. Blood vessel in retinal image plays a vital role in medical diagnosis of many diseases. Diabetic retinopathy is one of the diseases which damages the retina and leads to blindness. Segmentation of blood vessels is helpful for ophthalmologist and this paper presents a new automatic method to extract blood vessels with accuracy. This algorithm is comprises of optimized Gabor filter with local entropy thresholding for vessels segmentation under various normal and abnormal conditions. The frequency and orientation of Gabor filter are tuned to match that of a part of blood vessels to be enhanced in a green channel image. Segmentation of blood vessels pixels are classified by local entropy thresholding technique in this method .the performance of the proposed algorithm is evaluated by MATLAB software with DRIVE database. [2]. Wu, D.; Ming Zhang; Jyh-Charn Liu; Bauman, W., "On the adaptive detection of blood vessels in retinal images," Biomedical Engineering, IEEE Transactions on, vol.53, no.2, pp.341, 343, Feb.2006. This paper proposes an automated blood vessel detection scheme based on adaptive Contrast enhancement, feature extraction and tracing. Feature extraction ofsmall blood vessels is performed by using the standard deviation of Gabor filter responses. Tracing of vessels is done via forward detection, bifurcation identification and backward verification. Tests over twenty images show that for normal images, the true positive rate (TPR) ranges from 80% to 91% and their corresponding false positive rate (FPR) range from 2.8% to 5.5%. For abnormal images, the TPR ranges from 73.8% to 86.5% and the FPR ranges from 2.1%to5.3%,In comparison with two published solution schemes that were also based on the STARE database, our scheme has lower FPR for the reported TPR measure. [3]. “A supervised method for retinal blood vessel segmentation using line strength, multiscale Gabor and morphological features," Signal and Image Processing Applications (ICSIPA), 2011 IEEE International Conference on , vol., no., pp.410, 415, 16-18 Nov. 2011. The vascular tree observed in a retinal fundus images can provide clues for cardiovascular diseases. Its analysis requires the identification of vessel bifurcations and crossovers. This work use a set of trainable key point detection that we call combination of shifted filter responses or COSFIRE filters that are selective for a number of prototype bifurcations and demonstrate that such filters can be effectively used to detect bifurcations that are similar to the prototypical ones. The automatic configuration of such a filter select given channels of a bank of Gabor filters and determines certain blur and shift parameters. The response of a COSFIRE filter is computed as the weighted geometric mean of the blurred and shifted responses of the selected Gabor filters. The COSFIRE approach is inspired by the function of a specific type of shape- selective neuron in area V4 of visual cortex .Results: we ran experiments on three data sets and achieved the following results (a) a recall of 97.88% at precision of 96.64% on 40 manually segmented images provided in the DRIVE dataset, (b) a recall of 97.02% at precision of 96.53% on a set of 10 COSFIRE filters that we use are conceptually simple and easy to implement : the filter output is computed as the weighted geometric mean of blurred and shifted Gabor filter responses. They are versatile key point detectors as they can be configured with any given local contour pattern and are subsequently able to detect the same and similar patterns. [4]. S. Chaudhauri, S. Chatterjee, N. Katz, M. Nelson and M. Goldblum, "Detection of blood vessels in retinal images using two dimensional matched filters,” IEEE Trans. Medical imaging, vol. 8, no. 3, September 1989. Blood vessels usually have poor local contrast, and the application of existing edge detection algorithms yields results which are not satisfactory .an operator for feature extraction based on the optical and spatial properties of objects to be feature extraction based on the optical and spatial properties of objects to berecognized is introduced. The gray-level profile of the cross section of a blood vessel is approximated by a Gaussian-shaped curve. The concept of matched filter detection of signals is used to detect piecewise linear segments of blood vessels in these images. Twelve different templates that are used to search for vessel segments along all possible directions are constructed .various issues related to the implemented of these matched filters are discussed .the results are compared to those obtained with other methods.

PROPOSED METHOD:

In this chapter we are going to discuss about the concepts regarding system block diagram and brief description of each and every block and operation of project. Now each block diagram and its explanation is given below

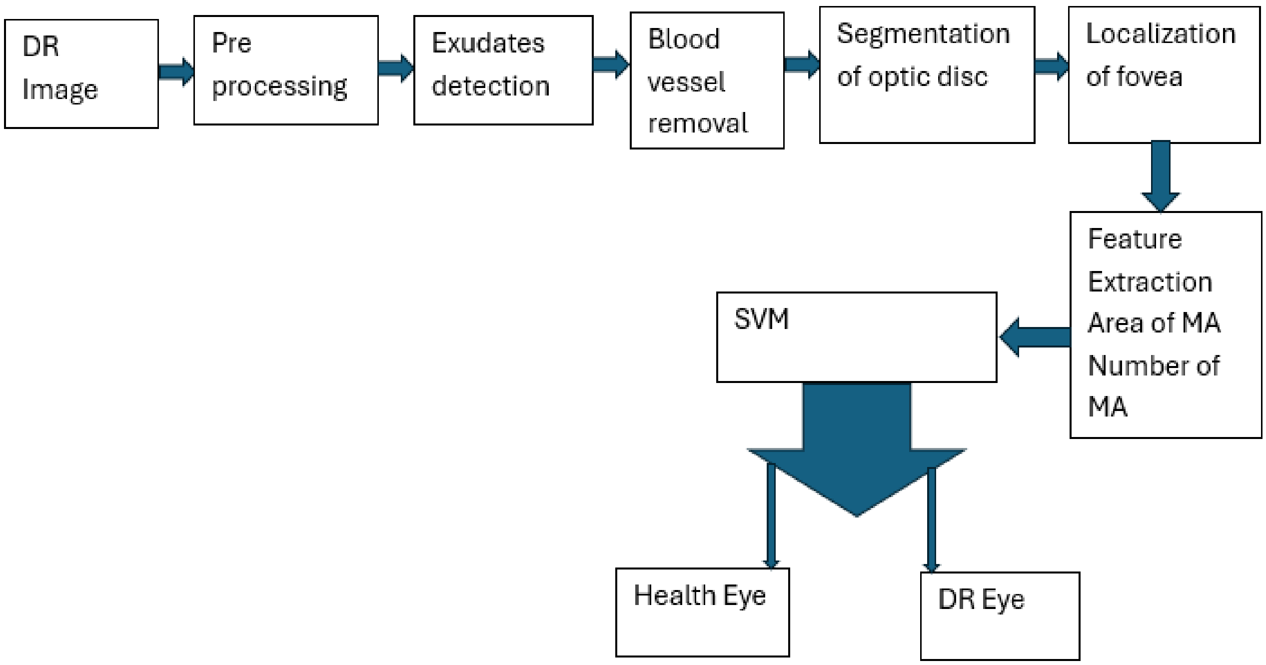


Fig1: Proposed block diagram

Diabetic retinopathy detection system consists three main steps: pre-processing techniques, feature extraction and classification techniques. There are verity of techniques have been proposed in literature for pre-processing, feature extraction and classification of DR. we propose different combination of pre-processing, feature extraction and classification techniques to improve DR detection. The architecture of the system is shown in above figure.

GRAY SCALECONVERSION: A colour image can have over 16 million different colours. A grayscale image has only 256 shades of grey. Grey scale images are composed exclusively of shades of grey, varying from black at the weakest intensity to white at the strongest. These images are also called monochromatic, denoting the absence of any chromatic variation. They are often the result of measuring the intensity of light at each pixel in a single band of the electro-magnetic spectrum. In photography, computing, and colourmetry, a grayscale or greyscale image is one in which the value of each pixel is a single sample representing only an amount of light, that is, it carries only intensity information. Images of this sort, also known as black-and- white or monochrome, are composed exclusively of shades of grey, varying from black at the weakest intensity to white at the strongest. Grayscale images are distinct from one-bit bi-tonal black-and-white images, which in the context of computer imaging are images with only two colors, black and white (also called bi-level or binary images). Grayscale images have many shades of gray inbetween. Grayscale images can be the result of measuring the intensity of light at each pixel according to a particular weighted combination of frequencies (or wavelengths), and in such cases they are monochromatic proper when only a single frequency (in practice, a narrow band of frequencies) is captured. The frequencies can in principle be from anywhere in the electromagnetic spectrum (e.g. infrared, visible light, ultraviolet,etc.). A colorimetric (or more specifically photometric) grayscale image is an image that has a defined grayscale color space, which maps the stored numeric sample values to the achromatic channel of a standard color space, which itself is based on measured properties of human vision. If the original color image has no defined color space, or if the grayscale image is not intended to have the same human-perceived achromatic intensity as the color image, then there is no unique mapping from such a color image to a grayscale image Thus, to simplify the process, the green channel image is converted to gray scale image. Even though, the loss of information is inevitable, such losses are not significant enough to reduce the efficiency of the automated classification system.

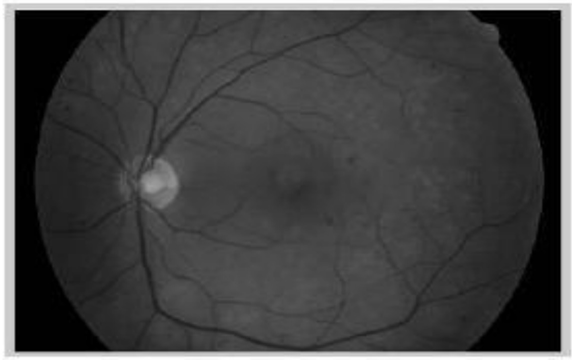


Fig:2 Gray Scale Image

The intensity of a pixel is expressed within a given range between a minimum and a maximum, inclusive. This range is represented in an abstract way as a range from 0 (or 0%) (Total absence, black) and 1 (or 100%) (Total presence, white), This notation is used in academic papers, but this does not define what "black" or "white" is in terms of colorimetry. Sometimes the scale is reversed, as in printing where the numeric intensity denotes how much ink is employed in half toning, with 0% speaking to the paper white (no ink) and 100% being a strong dark (fullink).

GREEN CHANNELEXTRACTION: In order to enhance the contrast of the retinal images, some information is commonly discarded before processing such as the red and blue components of the image. Consequently, only the green band is extensively used in the processing as it displays the best vessels/background contrast and the greatest contrast between the optic disc and the retinal tissue. In addition, the subsequent feature extraction process will be made simpler if the single channel image is used. Conversely, the red and the blue bands are hardly used by automated applications since much information is not clearly displayed in these channel images. Thus, the green pixel values are extracted from the input image and stored in the matrix form. Several abnormal retinal images from four different categories are collected from the hospitals and used in this work for disease identification. The abnormal retinal images collected from the hospitals cannot be directly classified by the automation techniques. The reason is twofold: (a) Lack of clarity in the anatomical features which is mainly due to the poor contrast of the raw image and (b) Large dimensions of the input image which accounts for the complexity of the system. Hence, suitable techniques must be adopted prior to the image classification process to overcome these drawbacks. The first drawback can be minimized by adopting suitable pre-processing techniques which can enhance the contrast of the input images.

HISTOGRAMEQUALIZATION: Adaptive histogram equalization (AHE) is a computer image processing technique used to improve contrast in images. It differs from ordinary 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. 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.

MORPHOLOGY OPERATION FOR NOISE REMOVAL: Binary images may contain numerous imperfections. In particular, the binary regions produced by simple thresholding are distorted by noise and texture. Morphological image processing pursues the goals of removing these imperfections by accounting for the form and structure of the image. These techniques can be extended to greyscale images.

Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. Morphological operations rely only on the relative ordering of pixel values, not on their numerical values, and therefore are especially suited to the processing of binary images. Morphological operations can also be applied to greyscale images such that their light transfer functions are unknown and therefore their absolute pixel values are of no or minor interest.

Morphological techniques probe an image with a small shape or template called a **structuring element**. The structuring element is positioned at all possible locations in the image and it is compared with the corresponding neighbourhood of pixels. Some operations test whether the element "fits" within the neighbourhood, while others test whether it "hits" or intersects the neighbourhood:

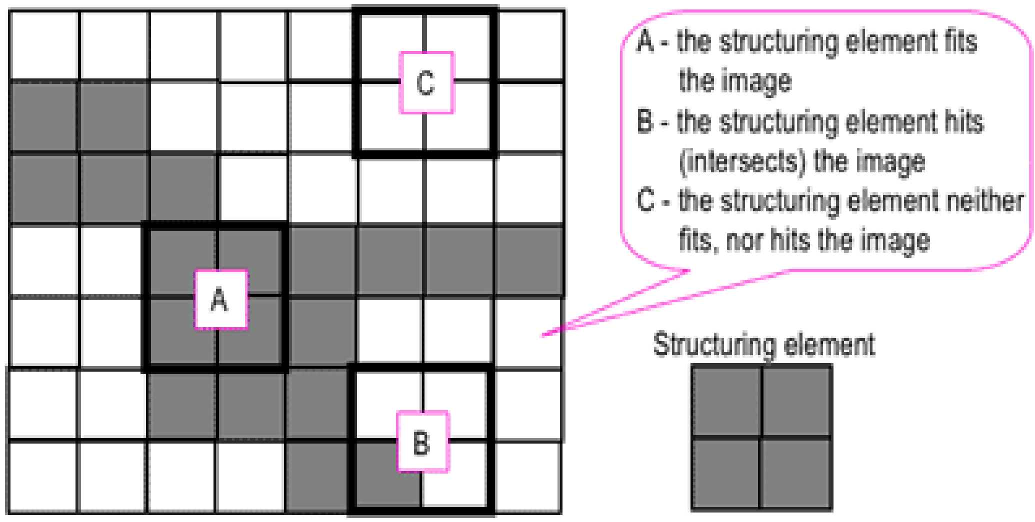


Fig3. Probing of an image with a structuring element
(white and grey pixels have zero and non-zero values, respectively).

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 **structuring element** is a small binary image, i.e. a small matrix of pixels, each with a value of zero or one:

- The matrix dimensions specify the *size* of the structuring element.
- The pattern of ones and zeros specifies the *shape* of the structuring element.
- An *origin* of the structuring element is usually one of its pixels, although generally the origin can be outside the structuring element.

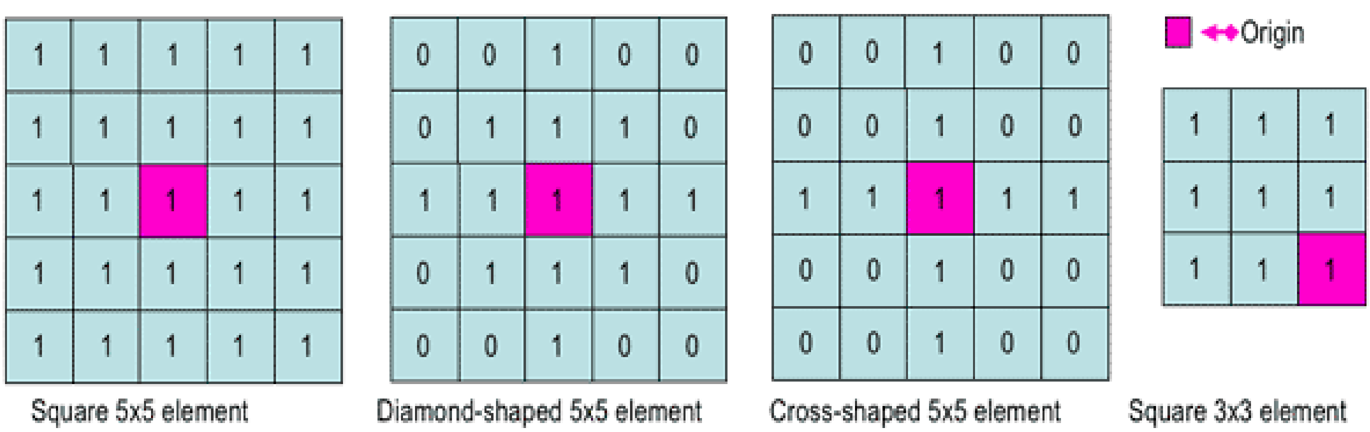
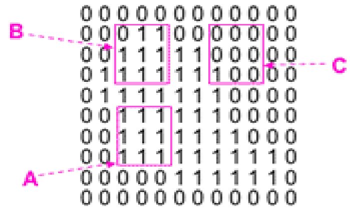


Fig4:Examples of simple structuring elements.

A common practice is to have odd dimensions of the structuring matrix and the origin defined as the centre of the matrix. Structuring elements play in moprphological image processing the same role as convolution kernels in linear image filtering.

When a structuring element is placed in a binary image, each of its pixels is associated with the corresponding pixel of the neighbourhood under the structuring element. The structuring element is said to **fit** the image if, for each of its pixels set to 1, the corresponding image pixel is also 1. Similarly, a structuring element is said to **hit**, or intersect, an image if, at least for one of its pixels set to 1 the corresponding image pixel is also 1.



$$s_1 = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \qquad s_2 = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

		A	B	C
fit	s_1	yes	no	no
	s_2	yes	yes	no
hit	s_1	yes	yes	yes
	s_2	yes	yes	no

Fig5: Fitting and hitting of a binary image with structuring elements s_1 and s_2.
Zero-valued pixels of the structuring element are ignored, i.e. indicate points where the corresponding image value is irrelevant.

Exudates detection After pre-processing, exudates are extracted from colour fundus image. Detection of exudates is necessary in detection of microaneurysm because the colour of exudates is same as microaneurysm. For detection of exudates, the pre-processed green channel image is obtained, which is further enhanced by ADHE. After that a marker has been generated using median

MEDIAN FILTERING: The median filter is an algorithm that is useful for the removal of **impulse noise** (also known as **binary noise**), which is manifested in a digital image by corruption of the captured image with bright and dark pixels that appear randomly throughout the spatial distribution. Impulse noise arises from spikes in the output signal that typically result from external interference or poor sensor configuration. This interactive tutorial explores the removal of impulse noise from a digital image using the median filter, and how the application of this and related filtering techniques affect the final appearance of the filtered image. The tutorial initializes with a randomly selected specimen (imaged in the microscope) appearing in the left-hand window entitled **Specimen Image**. Each specimen name includes, in parentheses, an abbreviation designating the contrast mechanism employed in obtaining the image. The following nomenclature is used: (**FL**), fluorescence; (**BF**), brightfield; (**DF**), darkfield; (**PC**), phase contrast; (**DIC**), differential interference contrast (Nomarski); (**HMC**), Hoffman modulation contrast; and (**POL**), polarized light. Visitors will note that specimens captured using the various techniques available in optical microscopy behave differently during image processing in the tutorial.

Adjacent to the **Specimen Image** window is a **Filtered Image** window that displays the image that has been filtered by a method selected in the **Choose A Filtering Method** pull-down menu. To operate the tutorial, select an image from the **Choose A Specimen** pull-down menu, and then select a filtering method from the **Choose A Filtering Method** pull-down menu. A choice between grayscale and color images is available in the tutorial, and the desired image collection may be selected by clicking on the **Grayscale Images** control or the **Color Images** control. The number of iterations entered into the text field located between the two sliders determines the number of times that the microscope image will be filtered by the selected processing method. Clicking the mouse cursor on the blue buttons appearing to the left and right of the iteration number text field will increase or decrease this value by one. The iteration number can also be adjusted by clicking on the text field input box, editing the number with the keyboard, followed by depressing the **Enter** key. The degree of artificial noise added to the specimen image can be increased or decreased by adjusting the **Noise Level** slider. The noise level added to the image is displayed directly above the slider as a percentage of the total number of image pixels. Visitors should examine the effects of the various filtering methods on the visual quality of the image after filtering, while varying the level of noise and the number of filtering iterations.

Potential sources of noise in digital imaging systems are quite numerous and can seriously degrade captured image quality. The amounts and types of noise that occur in the camera output signal are determined primarily by the camera sensor and its calibration, as well as by the electrical components in the camera itself, and auxiliary electronic devices used in conjunction with the camera. Common sources of radio frequency spikes and noise pulses include transformers, lamps, and other electronic devices. In some cases, it is possible to remove or minimize the effects of the most serious sources of noise through careful calibration and shielding of equipment. In other cases, it is preferable to filter such noise from images in the post-processing stage. The median filtering algorithm is a simple and viable approach to removing impulse noise from digital images.

In the tutorial, several noise-filtering algorithms are available for comparison. The first algorithm is **3 × 3 Box-Averaging** algorithm, which is a linear filter unrelated to the median filter. This filter computes an unweighted average of the pixel brightness values in a 3 × 3 neighborhood surrounding each pixel in the specimen image. The average value then defines the pixel brightness for each corresponding pixel in the filtered image. The box-averaging algorithm can be formulated as a convolution operation on the pixels of the original specimen image with the kernel**:**

BLOOD VESSEL REMOVAL: Blood vessel removal is preformed after exudates extraction. Firstly RGB image is converted into grey channel for better contrast. Grey scale conversion is done using principal component analysis (PCA). PCA is statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of correlation and dependence variables called principal components. PCA is powerful tool for analyzing data [9], [10]. It is basically used in dimensional reduction. Here, it is used to convert a 3-dimentional matrix (RGB) to 2-dimensional matrix (grey). Further CLAHE is used for contrast enhancement. CLAHE is mostly used in enhancement of low contrast retinal image. In case of CLAHE, a transformation function is derived from contrast limited procedure to each neighborhood pixel. CALHE is mainly developed to prevent over amplification of noise that ADHE raises [8]. Background is eliminated by averaging the enhanced image and subtracting it from the enhanced image. After background exclusion the image is converted to binary scale and retinal blood vessels are extracted.

SEGMENTATION OF OPTIC DISC: Segmentation of optic disc is done in two steps named as localization and detection. First we create template by blurring image using (6x6) window and extract the (80x80) pixels optic disc. Further, we extract the color components such as red, blue and green and store their histograms. This process is applied on all images in database and the average is obtained.

LOCALIZATION OF FOVEA For localization of fovea, pre-processed image has been used. The basic morphological operation is used to remove lesser area than 25 pixels, since fovea contains larger area than other structures. Fovea localization is essential since it helps to reduce the false detection of microaneurysm. Its area varies from image to image.

MICROANEURYSM: Microaneurysm has been detected from fundus image by subtracting the exudates, blood vessels, optic disc and fovea from pre-processed image.

FEATURE EXTRACTIONS: There are two features of microaneurysm, such as area of microaneurysm and number of MAs have been extracted from fundus images. Area of microaneurysm is calculated as total number of white pixels in extracted image of microaneurysms. The number of microaneurysms is calculated as number of discontinuity from white pixel to black pixel.

CLASSIFICATION: SVM classifier has been used for DR detection. SVM classify the image into two classes such as DR eye and healthy eye. Parameters of SVM classifier has been calculated based on features of microaneurysm.

SUPPORT VECTOR MACHINES: SVMs are the most popular algorithm for classification in **machine learning algorithms**. Their mathematical background is quintessential in building the foundational block for the geometrical distinction between the two classes. We will see how Support vector machines work by observing their implementation in Python and finally, we will look at some of the important applications.

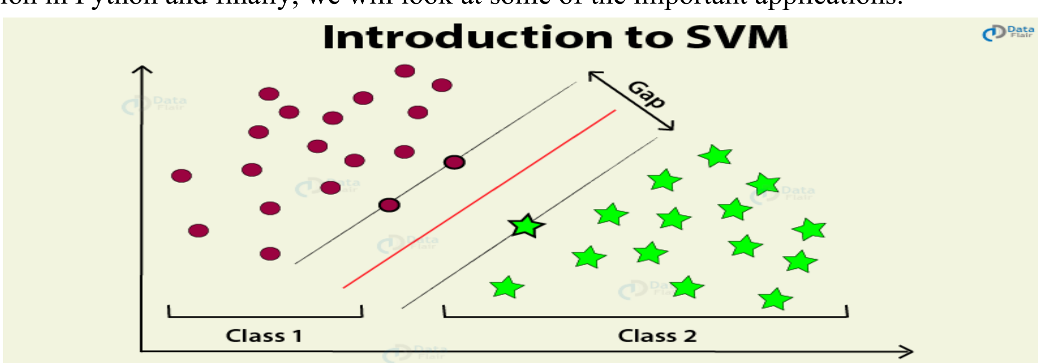


Fig6 SVM Classes

Support Vector Machines are a type of supervised machine learning algorithm that provides analysis of data for classification and regression analysis. While they can be used for regression, SVM is mostly used for classification. We carry out plotting in the n-dimensional space. Value of each feature is also the value of the specific coordinate. Then, we find the ideal hyperplane that differentiates between the two classes.

These support vectors are the coordinate representations of individual observation. It is a frontier method for segregating the two classes.

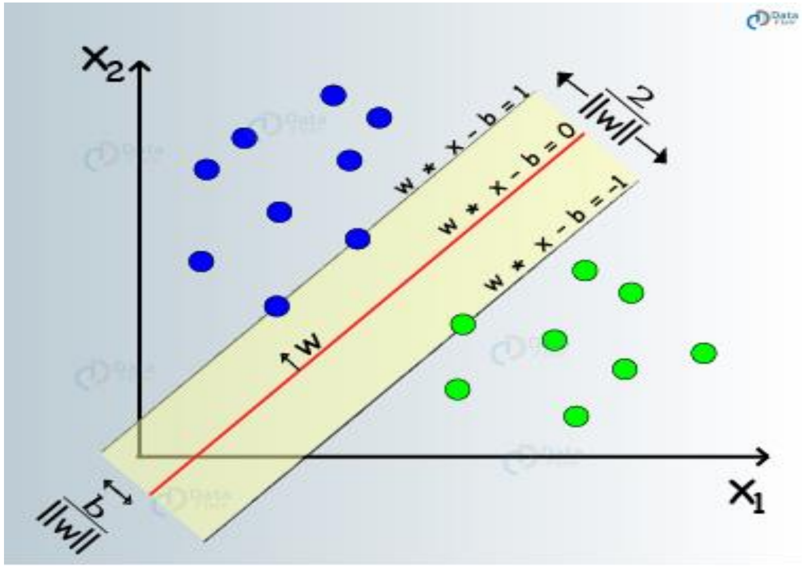


Fig7: SVM linear

RESULTS:

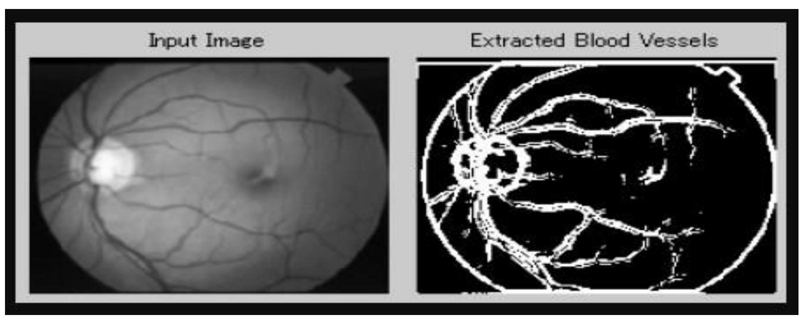


Fig. a Extracted blood vessels

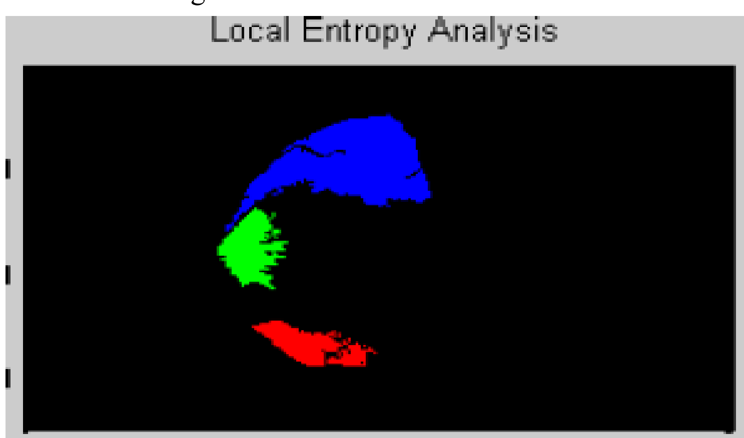


Fig b: Entropy Analysis

ADVANTAGES:

Early Detection

- Microaneurysms are the earliest signs of diabetic retinopathy.
- Enables diagnosis before severe vision damage occurs.

High Diagnostic Accuracy

- Quantitative features such as number and area improve reliability.
- Reduces false positives and misclassification.

Reduced Ophthalmologist Workload

- Automates initial screening process.
- Allows specialists to focus on severe cases.

Conclusion: This project presented an improved scheme for the detection of diabetic retinopathy by accurate determination of number and area of microaneurysm. The achieved value of sensitivity and specificity shows that the proposed diagnostic system is better for non-proliferative diabetic retinopathy detection. The proposed method enables quantitative analysis by measuring both the count and spatial area of microaneurysms, which helps in precise grading of diabetic retinopathy stages. By processing colour fundus images through image enhancement, segmentation, and feature extraction techniques, the system reduces dependence on manual examination and minimizes human error.

Future work: Future work of this paper is to propose a proliferative diabetic retinopathy detection system by considering cotton wools and abnormal blood vessels as features from color fundus images. DR detection system could be extended to multi class diabetic retinopathy classification, namely to classify into healthy, mild non-proliferative, moderate non-proliferative, severe non-proliferative, and proliferative diabetic retinopathy by using Feed Forward Neural Network, Radial Basis Function Neural Network (RBFNN) and SVM.

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