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IDENTIFICATION OF DIABETIC RETINOPATHY

[1]Mr.A.Chandra Mouli, M.tech, (Ph.d), [2] D. Vishnu Priya,[3] P. Divya Keerthi, [4]K.Yeshwanth, [5] K. Jaya Kumar
1Assistant Professor ,CSE, PSCMRCET, Vijayawada, Andhra Pradesh
[2]Student, CSE, PSCMRCET, Vijayawada, Andhra Pradesh
[3]Student, CSE, PSCMRCET, Vijayawada, Andhra Pradesh
[4]Student, CSE, PSCMRCET, Vijayawada, Andhra Pradesh
[5]Student, CSE, PSCMRCET, Vijayawada, Andhra Pradesh

***Abstract**:* Diabetic Retinopathy is a disorder of the retina as a result of the impact of diabetes on the retinal blood vessels. It is the major cause of blindness in people like age groups between 20-60. As polygenic disorder proceeds, the eyesight of a patient may commence to deteriorate and causes blindness. In this proposed work, the existence or lack of retinal exudates are identified using Machine Learning(ML). To detect the occurrence of exudates features like Mean, Standard deviation, Centroid, and Edge Strength. Image segmentation is a technique of partitioning image pixels depending on one Support Vector Machine (SVM) which allows pixels to remain in various categorizations with multiple degrees of membership.

Index Terms **- Machine Learning, Segmentation**

I. INTRODUCTION

The familiar cause of blindness is diabetes these days in working age populations. Many patients eyesight can be affected due to diabetes[1]. People do not know the cause of blindness due to diabetes and are also unaware about different diseases caused by diabetes. Patients can suffer from dieses like cataract, glaucoma, bleeding of blood vessels, etc[2]. Any damage caused to the blood vessels in the eye due to diabetes is called as diabetic retinopathy. Diabetic Retinopathy is a micro vascular difficulty which can lead to several turns in the retina. There are many changes which can occur like change in the diameter of blood vessels, growth of new blood vessels, micro aneurysms, hemorrhage, exudates, etc. These changes must be detected at an early stage. Diabetic Detection(DD) is a complication of DR. Diabetic Detection(DD) is defined as swelling of the eye retina in diabetic patients due to leakage of fluid within the central macula from the dilated small blood vessels.

II. EXISTING SYSTEM

The pixels that are having similar ranges within the level were identified and the pixels were grouped. The basis could be, for example, pixel intensity, gray level texture, or color. At each stage and for each region, we check if there are unclassified pixels in the 8- neighbourhood of each pixel of the region border. Before classifying the region homogeneity.

- **Ophthalmoscope (Indirect and Direct):**Direct ophthalmoscope is the examination method performs by the specialist in a dark room. A beam of light is shined through the pupil using an ophthalmoscope. This allows the specialist to view the back of the eyeball. Direct ophthalmoscope is performed with a head or spectacles-mounted source of illumination positioned in the middle of the forehead. A bright light is shined into the eye using the instrument on the forehead. The condensing lens is placed on the eye to intercept the fundus reflex. A real and inverted image of the fundus will form between the tester and the patient.
- **Fluorescein Angiography:**Fluorescein angiography is a test that permits the blood vessels in the back of the eye to be photographed as a fluorescent dye is injected into the bloodstream via the hand or arm. The pupils will be dilated with eye drops and the yellow dye (Fluorescein Sodium) is injected into a vein in the arm. It is used to examine the blood circulation of the retina using the dye tracing method.
- **Fundus Photography:**Fundus photography is the usage of a fundus camera to photograph the regions of the vitreous retina, choroid, and optic nerve. Fundus photographs are only considered medically necessary where the results may influence the management of the patient. In general, fundus photography is performed to evaluate abnormalities in the fundus, follow the progress of a disease, plan the treatment for a disease, and assess the therapeutic effect of recent surgery. The proposed system takes the images for imaging processing that were taken from the fundus camera.

III. EASE OF USE

To develop identification of diabetic retinopathy we will use four steps:

- Preprocessing
- Segmentation
- Feature Extraction
- Classification

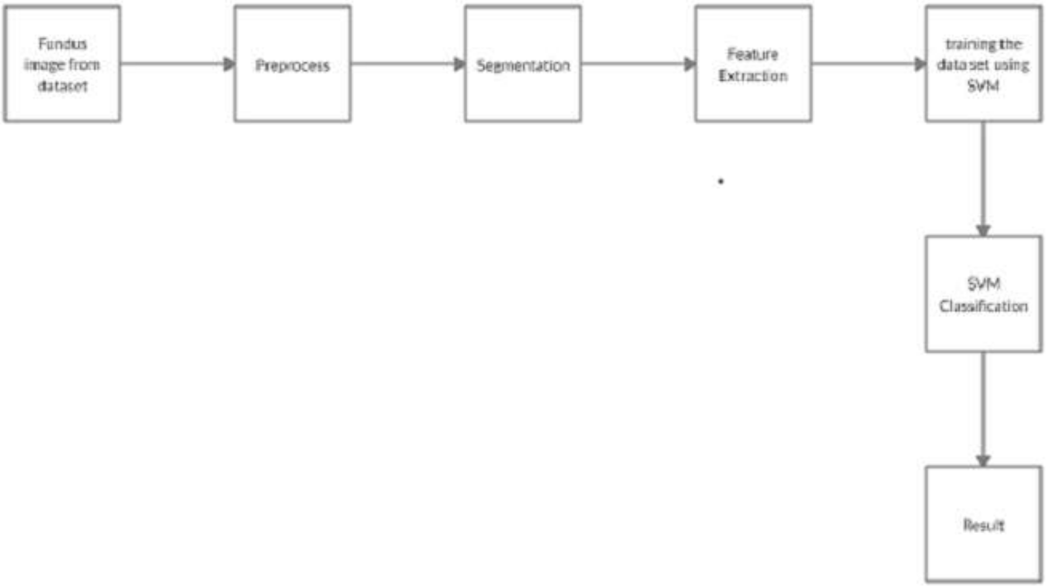


figure:3.1 proposed system for diabetic retinopathy

3.1 PREPROCESSING

To detect the presence of diabetic retinopathy, the steps followed are pre-processing, segmentation, and feature ranking. Pre-processing is required to ensure that the dataset is consistent and displays only relevant features. This step is necessary to simplify the workload of the following processes. Next, the images are segmented to differentiate between normal and abnormal substances. Green Channel of the three color channels in the image (Red, Green, and Blue) the contrast between the blood vessels, exudates, and hemorrhages are best seen in the green channel and these channels neither under- illuminated nor over-saturated like the other two. Hence, we have extracted only the green channel for analysis and classification given as an illustrative example in Figure 3.1.1.

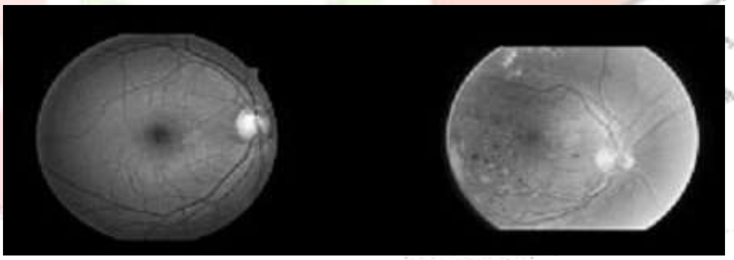


figure: 3.1.1 separation of the green channel of an image

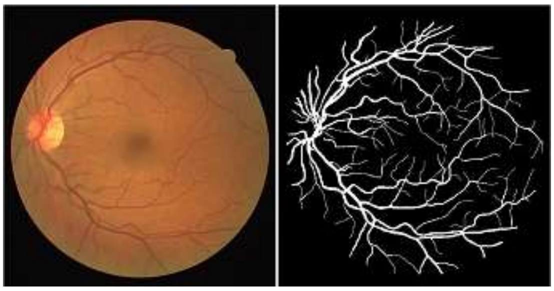
3.2 SEGMENTATION

Segmentation has 3 following stages:

- Blood vessel detection
- Optic disc detection
- Exudates detection

3.2.1 Blood Vessel Detection

We can select the green component for blood vessel extraction because the vessels have high contrast. The Blood vessels were segmented using morphological operations. Morphological image processing is a collection of non-linear operations related to morphology of features in an image. Morphological operations can also be applied to gray scale images. Morphological operation of a binary image is conducted by considering compound operations like dilation, erosion, opening, and closing as filters.They may act as filters of shape. For example, opening with a disc arranging element smoothes the corners from the inside, and closing with a disc smoothes corner from the utside. But these operations also can filter out from an image any details that are smaller in size than the arranging element, e.g. opening is filtering the binary image at a scale defined by the size of the arranging element. Only those portions of the image that fit the arranging element are passed by the filter; smaller structures are blocked and excluded from the output image. The size of the arranging element is most important to eliminate noisy details but not to damage objects of interest. Figure 3.2.1.1 shows the segmented blood vessel using the morphological operation.

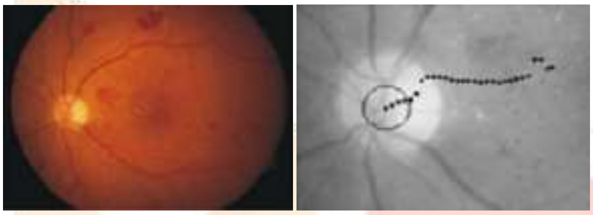


(a) (b)

figure: 3.2.1.1 (a) input image (b) blood vessel segmentation

3.2.2 Optic Disc Detection

Optic detection is one of the main tasks in the detection of exudates. Because optic disc has affiliate characteristics of exudates such as brightness, color, and contrast. We use Level set segmentation to segment the Optical disc region in the image. The first step in the level set is to select a set of levels. Level selection is based on some user criteria. The initial region begins at the exact location of the pixels in the levels. The pixels that are having similar ranges within the level were identified and the pixels were grouped. At each stage and for each region, we check if there are unclassified pixels in the 8- neighborhood of each pixel of the region border. Before classifying the region homogeneity is verified. The two regions are merged based on the arithmetic mean and the Standard Deviation. Figure 3.2.2.1 shows the result of optic disc detection.

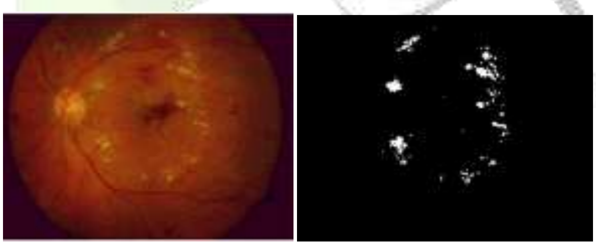


(a) (b)

figure: 3.2.2.1 (a) input image (b) optic disc detection

3.2.3 Exudates Detection

The exudateS detection in retinal images will be helpful in the early identification of Diabetic Retinopathy and it can help provide treatment for the patients. Exudates can be recognized on the ophthalmoscope as areas with hard white or yellowish colors with varying sizes, shapes, and locations. They normally appear near the leaking capillaries. In this proposed method, the exudates were detected using thresholding along with morphological operations. When the thresholding is applied to the image, OD and Exudates were separated from the image. The morphological operation is used after the thresholding process, to eliminate OD. Finally exudates were separated from the retinal image. Figure 3.2.3.1 shows the result of exudates segmentation.



(a) (b)

figure: 3.2.3.1 (a) input image (b) exudates detection

3.3 Feature Extraction

The features were extracted using Gabor and GLCM feature extraction methods. The Gabor and the GLCM features give the texture information from the images. The texture-based information means, the information regarding the shapes of the objects in the images.

3.3.1 GLCM Feature Extraction

A Gray Level Co-occurrence Matrix (GLCM) accommodates information about the locations of pixels having similar gray level values. A co-occurrence matrix is a two dimensional array, P, in which both the rows and the columns defend a set of possible image values. A GLCM Pd [i, j] is described by first specifying a displacement vector d=(dx, dy) and counting all pairs of pixels separated by d having gray levels i and j. From the co-occurrence matrix obtained, we were extracting the 12 different statistical features such as Contrast, Correlation, Cluster prominence, Cluster shade, Dissimilarity, Energy, Entropy, Homogeneity, Maximum probability, Sum of squares, Autocorrelation, Inverse different Moment.

Contrast: Contrast is a measure of the local alternations present in an image.

$$C(k,n) = \sum_i \sum_j (i-j)^k P_d[i,j]^n$$

Homogeneity: A homogeneous image will consequence in a co-occurrence matrix with a union of high and low P [i, j]'s.
Entropy: Entropy is a measure of information content. It measures the dissonance of intensity distribution.

$$C_e = -\sum_i \sum_j P_d[i,j] \, |n \, P_d[i,j]$$

Correlation: The Correlation is a measure of image linearity.

$$eC_c = \frac{\sum_i \sum_j [ij[P_d[i,j]] - \mu_i \mu_j}{\sigma_i \sigma_j}$$

where $\mu_i = \sum i \, P_d[i,j] = \sum i^2 P_d[i,j] - \mu i^2$
The correlation will be higher if an image contains a considerable quantity of linear struct

Maximum Probability: This is simply the largest entry in the matrix, and corresponds to the strongest reaction.

$$C_m = max_{i,j} P_d[i,j]$$

3.4 Classification

Support vector machines are supervised learning models with associated learning algorithms that examine data and perceive patterns used for classification and regression analysis. The basic SVM takes a set of input data and predicts the output, which forms two possible classes. This will make it a no probabilistic binary linear classifier. Classification accuracy is computed. SVM maps input vectors to a higher dimensional vector space where an optimal hyperplane is constructed. Among the many hyperplanes, there is only one hyperplane that maximizes the distance between itself and the nearest data vectors of each category. This hyperplane, which maximizes margin is called the optimal separating hyperplane and the margin is defined as the sum of the distances of the hyperplane to the closest training vectors of each category.

Expression for hyperplane

WX +0

X – Set of training vectors

W – Vectors perpendicular to the separating hyperplane

B – counteract parameter which allows the increase of the margin

The classification of the images is done by using the SVM classifier. 40 images were provided as training data set along with the labels. SVM will test, the test image features based on the training feature set and labels belonging to each training image. Since here we have used Binary SVM Classifier, all the classes were grouped into two disjoint groups classes. This grouping is then used to train an SVM classifier in the root node of the decision tree, Using the samples of the first group as negative examples and the samples of the second group as positive examples. Using this the normal and the defected retina were identified. If the result of the classifier is a normal image, then there is no need for segmentation. If the result of the classifier is abnormal, then the particular defect such as exudates were segmented using the relevant segmentation technologies.

IV. PERFORMANCE METRICS

A total of 40 images are selected from all two databases at random and for those images, a comparison between the proposed method and ground truth for the lesion. The performance of the proposed system is evaluated based on four measures, namely,
True positive (TP) indicates that the patient suffers from the disease and the test result was also positive.
False-positive (FP) indicates that the patient do not suffer from the disease and was diagnosed as positive.
True negative (TN) indicates that the patient do not suffer from the disease and was diagnosed as negative.
False-negative (FN) indicates that the patient suffers from the disease but diagnosed as negative.

Sensitivity: TP represents the fraction of pixels correctly classified as bright lesion pixels. This measure is also known as sensitivity.

$$Sensitivity = \frac{TP}{TP+FN} \times 100 \quad (1)$$

Specificity: Specificity is defined as the percentage of normal images classified by the system Accuracy in percentage is the measure of

$$Specificity = \frac{TN}{TN+FP} \times 100 \quad (2)$$

Accuracy: Accuracy is the percentage of correctly classified normal and abnormal images

$$Accuracy = \frac{TP+TN}{(TP+FN+TN+FP)} \times 100 \quad (3)$$

V. RESULTS

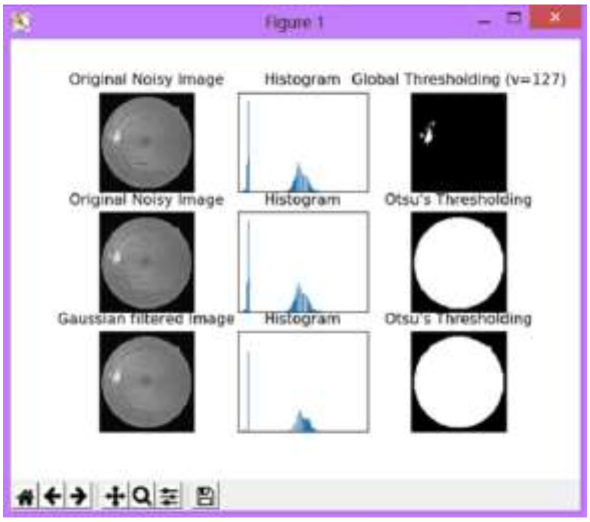


figure: 5.1 thresholding for input image

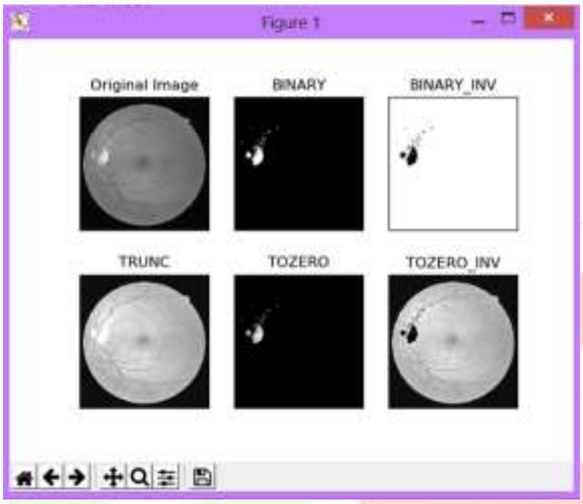


figure:5.2 binary, binary inversion, truncate, tozero, tozero inversion methods applied on original image

VI. CONCLUSION

Microneurysm segmentation instinctively done by using mathematical morphology is effective to attain its value. Exudates segmentation results are automatically performed by using max tree and attribute filtering to reduce noise and obtain exudates candidates. The method improved the previous researcher's methods. Feature extraction using exudates feature values, microaneurysm, entropy green channel, green channel homogeneity, the statistical value of saturation images (mean, standard deviation, kurtosis, skewness) can be used a reference for classification. Performance of Support Vector Machine was in excellent category with a sensitivity value of 96.9%, Specificity 100%, positive predictive value 100%, negative predictive value (NPV) The development of image processing methods to a mature level where the results can be transferred from the research laboratories to practice requires the following: accepted and applied protocols for evaluating the methods, protocols that are similar to the strict regulations in the medical treatment, and medical research.

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