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# DIABETICS RETINOGRAPHY

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***Abstract:*** The automatic exudate segmentation in color retinal structure pictures is a vital task in laptop assisted designation and screening systems for diabetic retinopathy. during this paper, we have a tendency to gift a location-to-segmentation strategy for automatic exudate segmentation in color retinal structure pictures, which has 3 stages: anatomic structure removal, exudate location and exudate segmentation. In anatomic structure removal stage, matched filters primarily based} main vessels segmentation technique and a strikingness based point segmentation technique area unit planned. the most vessel and point area unit then removed to eliminate the adverse effects that they bring about to the second stage. within the location stage, we have a tendency to learn a random forest classifier to classify patches into 2 classes: exudate patches and exudate-free patches, within which the histograms of completed native binary patterns area unit extracted to explain the feel structures of the patches. Finally, the native variance, the dimensions previous regarding the exudate regions and therefore the native distinction previous area unit won't to phase the exudate regions out from patches that area unit classified as exudate patches within the location stage. we have a tendency to assess our technique each at exudate-level and image-level. For exudate-level analysis, we have a tendency to check our technique on e-ophtha EX dataset, that provides element level annotation from the specialists. The experimental results show that our technique achieves seventy six in sensitivity and seventy fifth in positive prediction price (PPV), that each beat the state of the art ways considerably. For image-level analysis, we have a tendency to check our technique on DiaRetDB1, and succeed competitive performance compared to the state of the art ways.

*Index Terms –*

## I. INTRODUCTION

Retinopathy is a condition profound in diabetic patients, which contributes to 5% of the total blindness globally. The high level of blood sugar damages the retinal blood vessels by altering the blood flow. In the early stages of Diabetic Retinopathy (DR) there are no symptoms and hence it is not possible to detect the disease without examination. Exudates are one of the main signs for the presence of DR, which occurs due to leakage of fats and proteins as yellow masses in various sizes. If the exudates are not diagnosed earlier, it may lead to complete blindness by the accumulation of exudates in the fundus oculi. Frequent screening procedure is necessary to detect early condition of DR. A major limitation faced by the clinicians is screening a large number of images, which is very expensive and also open to human error. In order to solve this problem a Computer Aided Diagnosis (CAD) is necessary to identify the stages of DR. The aim of this work is to develop CAD system to differentiate the abnormal images from the normal fundus images and also grade the abnormal images as mild moderate and severe.

Diabetic Retinopathy (DR) is one of the leading causes of visual impairment in the developed world. It is provoked by complications of diabetes mellitus. Although diabetes does not necessarily involve vision impairment, about 2% of the patients affected by this disorder are blind and 10% undergo vision degradation after 15 years of diabetes as a consequence of DR complications. DR patients perceive no symptoms until visual loss develops. So to ensure that the treatment is received on time, diabetic patients need annual eye fundus examination using digital retinal photography. The aim of the screening programs is to detect potentially sight threatening diseases, sufficiently early to allow timely and effective treatment. The estimated prevalence of diabetes is forecasted to increase from 171 million in 2000 to 336 million in 2030. There is consequently considerable interest in the potential of automated retinal image analysis, to mitigate this projected increase in the screening workload. Classification of the severity of diabetic retinopathy and quantification of diabetic changes are vital for assessing the therapies and risk factors for this frequent complication of diabetes. The employment of digital images for diagnosis of eye diseases could be exploited for computerized early detection of DR. A system that could be used by non-experts to filtrate cases of patients not affected by the disease, would reduce the specialists' workload, and increase the effectiveness of preventive protocols and early therapeutic treatments. Furthermore, it would result in economic benefits for public health systems, since cost effective treatments associated with early illness detection leads to remarkable cost savings.

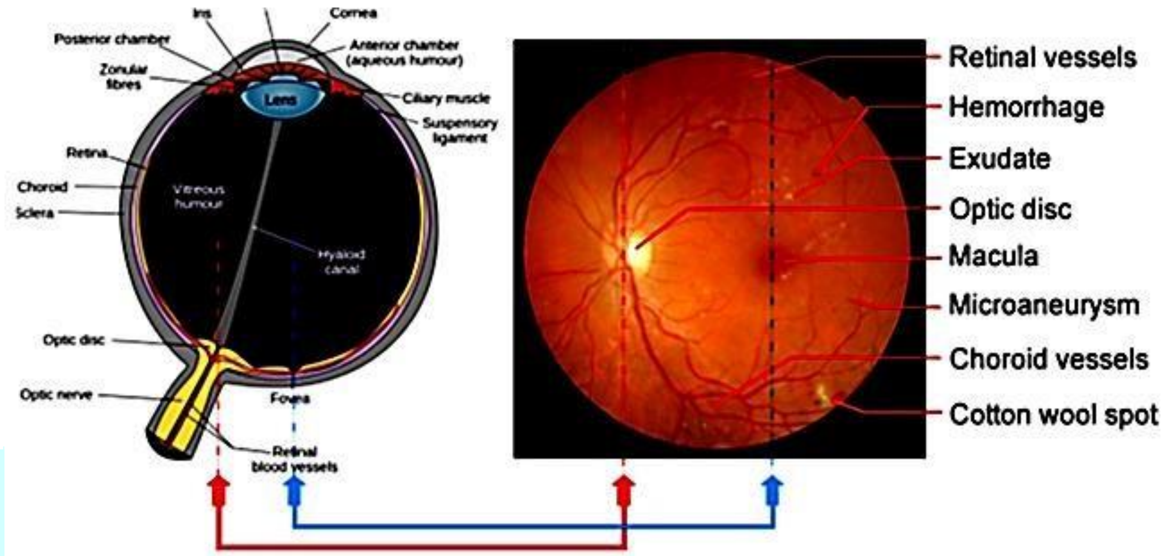



Figure1: Retina

**SYSTEM STUDY**

2.1 Existing System

In the past, various exudate segmentation methods have been proposed. Alireza Osareh et al [9] proposed a computational intelligence based approach for detection of exudates in DR images. The pre-processing steps involved in this approach are color normalization and contrast enhancement. The preprocessed images are segmented using Fuzzy C Means clustering. A set of initial features that are extracted to classify the segmented regions into exudates and non-exudates are color, size, edge strength and texture. Genetic based algorithm is used to rank and identify a subset of features for better classification results. A multilayer neural network classifier is used for classification. The images were collected from Bristol Eye hospital for testing the algorithm. Doaa Youssef et al [10] proposed a fast and accurate method for early detection of exudates in fundus photographs. For noise reduction median filter is used and the contrast enhancement is done using top hat transform. The optic disc is extracted using Hough transform. Since this method is based on contour detection, snakes algorithm is used.

**2.1.2 Problem Definitions**

The blood vessel is detected using morphological operations. The blood vessels and optic disc are eliminated from the edge detected image, to obtain an initial estimate of the exudates. Small exudate candidates are directly computed from the green channel of the original image by means of morphological top-hat transform. The features are extracted from the candidates and random forest method is used to perform classification.

### 2.2 Proposed System

In the proposed method, preprocessing step enhances the quality of the image. Further to improve the contrast between exudate and non-exudate regions, shade correction is performed. The second stage involves segmentation of exudates from the green channel image after removal of blood vessels and optic disc. The
GLCM features are extracted from the segmented region. Using the extracted feature five classifiers SVM, SCGBPN, GRN, PNN, and RBF are trained and tested for obtaining the best classifier.

#### 2.2.1 Features In Proposed System:

It would result in economic benefits for public health systems, since cost effective treatments associated with early illness detection leads to remarkable cost savings. It works really well with clear margin of separation. It is effective in high dimensional spaces. It is effective in cases where number of dimensions is greater than the number of samples. It uses a subset of training points in the decision function (called support vectors), so it is also memory efficient.

## I. SYSTEM DESIGN AND ANALYSIS

### 3.1 File Design

The design base files are the most important of the app. The performance of the app depends on how the app is design. It has been given at most attention to reduce the size of files and redundancy. At the same time all the files are design to incorporate all relevant information regarding each entity. A single database with information about all the entities will make the app more complicated. The functions and structure of each of the database files are given below. In this the file contains the details of industries with their rates for low, medium and high quality material. The rate of materials varies depending on the input and quality.

### 3.2 Input Design

The Input design is mainly concerned with an input screen in the software. In the input design, user oriented inputs are converted into a computer based system format. User can also select desired options from the menu, the provides all possible facilities. Also the important input format is designed in such a way that accidental errors are avoided. The user has to input only just the minimum data required, the also helps in avoiding the errors that the users may make. Accurate designing of the input format is very important in developing efficient software.

- The image should be given as image.
- The user details with email, phone no, age and gender is given as input.

### 3.3 Output Design

Outputs from computer systems are required primarily to communicate the results of processing to users. They are also used to provide permanent copy of the results for later consultations. The outputs are needed to be generated as a hard copy and as well as queries to be viewed on the screen. Keeping in view these outputs, the format of the output is taken from the outputs, which are currently being obtained after a processing. The standard printer is to be used as output media for hard copies. The main objective of output design is to interrupt and communicate the result of the computer part of the system to user in a form, which they meet their requirements and also to communication the output specification to the programmers in a way, this is unambiguous, comprehensive

- The segmented 6 layer output with laser classification.
- The unit value of the infected region.
- Level of severity.

### 3.5 Module Description

A system development lifecycle (SDLC) adheres to important faces that are essential for developers, such as planning, analysis, and implementation and are explained in the section below. A number of system development life cycle models have been created: waterfall, spiral, build and fix, rapid prototyping, incremental, synchronize and stabilize. The oldest of these and the best known is the waterfall model: A sequence of stage in which the output of each becomes the input for the next.

### 3.5.1 Image Pre-Processing

The green band is largely used for identification of exudates, since it gives more information than red and blue bands. The green channel image is filtered by applying a morphological opening as structuring element in order to remove vessel central light reflex, since it may contribute to false detection of exudates. Background homogenization is done using arithmetic mean kernel which smoothens the intensity values uniformly.

### 3.5.2 Exudate Detection

The exudates are segmented by removing blood vessels and optic disc from the green channel image extracted from the fundus image. The steps for exudate detection are as follows.

**Step1. Blood vessel segmentation:**

Blood vessels are prone to cause bright lesion like appearance during the segmentation of exudates. Hence it is removed in order to reduce false positive and to improve the accuracy of exudate segmentation. Fuzzy CMeans (FCM) clustering algorithm is used to segment the blood vessel since it can retain more information of the dataset. FCM is a data clustering technique wherein each data point belongs to a cluster to some degree that is specified by a membership grade [10]. It is based on minimization of the objective function given in equation (1)

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^{m} \; \|x_i - c_j\|^2 \qquad 1 \le m \le \infty \qquad (1)$$

where m is any real number greater than 1, uij is the degree of membership of xi in the cluster j, xi is the ith of d-dimensional measured data, cj is the d-dimension centre of the cluster, and ||*|| is any norm expressing the similarity between any measured data and the centre.

**Step2. Optical disc segmentation:**

The segmentation of optic disc is crucial since it is circular in shape with high contrast and is similar to exudates. The optic disc is removed using a circular mask.

**Step3. Exudate segmentation:**

An entropy filtering is performed on the pre-processed image clearly segments blood vessels, optic disc and exudates. For detecting the exudates, the blood vessels segmented in step 1 and the optic disc obtained in step 2 are subtracted from the filtered image.

### 3.5.3 Feature Extraction

The extraction of features is essential in order to extract the desired information and discard the undesired information. The textural feature utilizes the contents of the GLCM to provide the measure of variation in intensity at the pixel of interest. The features are extracted by pairwise spatial co-occurrences of pixels separated by some angle and distance which are tabulated using the GLCM. The GLCM consist of an NxN matrix, where N is the number of gray levels in the image. The Four GLCM features that are selected as the feature set are correlation, cluster shade, dissimilarity and entropy.

Correlation [16] is the gray level linear dependence between the pixels at a specified position to each other as in equation (2).

$$\text{Correlation} = \frac{\sum_i \sum_j (i,j) p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \qquad (2)$$

Cluster shade [17] is a measure of the skewness of the matrix or lack of symmetry. When the value of cluster shade is higher, the image is not symmetric with respect to the texture value. The cluster shade is estimated using equation (3)

$$\text{Cluster shade} = \sum_{i,j}^{i,j} \left( (i - \mu_i) + (j + \mu_j) \right)^3 c(i,j) \quad (3)$$

C (i,j) – is the (i,j) the entry in co-occurrence matrix C

$\sum_i$ means $\sum_{i=1}^{i=M}$ where M is the number of rows

$\sum_j$ means $\sum_{j=1}^{j=N}$ where N is the number of columns

$\sum_{i,j}$ means $\sum_i , \sum_j$

$\mu_i$ is defined as $\mu_i = \sum_i i \sum_j c(i, j)$

$\mu_j$ is defined as $\mu_j = \sum_i j \sum_j c(i, j)$

Dissimilarity [18] is a measure that defines the variation of grey level pairs in an image. It is computed as in (4)

$$\text{Dissimilarity} = \sum_{i,j} |i - j| p(i, j) \quad (4)$$

It is expected that these two measures behave in the same way for the same texture because they calculate the same parameter with different weights. Contrast will always be slightly higher than the dissimilarity value. Dissimilarity ranges from [0, 1] and obtain maximum when the grey level of the reference and neighbour pixel is at the extremes of the possible grey levels in the texture sample. Entropy [19] shows the amount of information of the image that is needed for the image compression. Entropy measures the loss of information in a transmitted image as in equation (5).

$$\text{Entropy} = -\sum_{i,j} p(i, j) * \log(p(i, j)) \quad (5)$$

A completely random distribution would have very high entropy because it represents disorder. Solid tone image would have an entropy value of 0.

### 3.5.4 Classification

Classification helps to identify the classes with similar features. GLCM features such as correlation, cluster shade, dissimilarity, and entropy are extracted. Based on the features the classifier classifies the images as normal, mild, moderate and severe. The classifier is selected by testing different classifier performances. The classifiers Support Vector Machine (SVM), multilayer network Scaled Conjugate Gradient – Back Propagation
Network (SCG-BPN) and Generalized Regression Network (GRN), Probabilistic Neural Network (PNN), Radial Basis Network (RBF) are tested and found SVM classifier is more accurate and have high performance.

### 3.5.5 Support Vector Machine

Support Vector Machine" (SVM) is a supervised machine learning algorithm which can be used for both classification or regression challenges. However, it is mostly used in classification problems. In this algorithm, we plot each data item as a point in n-dimensional space (where n is number of features you have) with the value of each feature being the value of a particular coordinate.

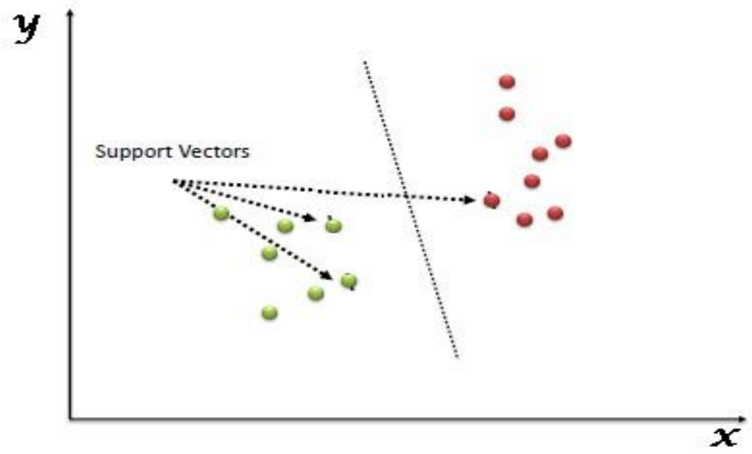



Figure2: Support Vector machine process

How does it work?

Above, we got accustomed to the process of segregating the two classes with a hyper-plane. Now the burning question is "How can we identify the right hyper-plane?". Don't worry, it's not as hard as you think! Let's understand:

4 **Identify the right hyper-plane (Scenario-1):** Here, we have three hyper-planes (A, B and C). Now, identify the right hyper-plane to classify star and circle.

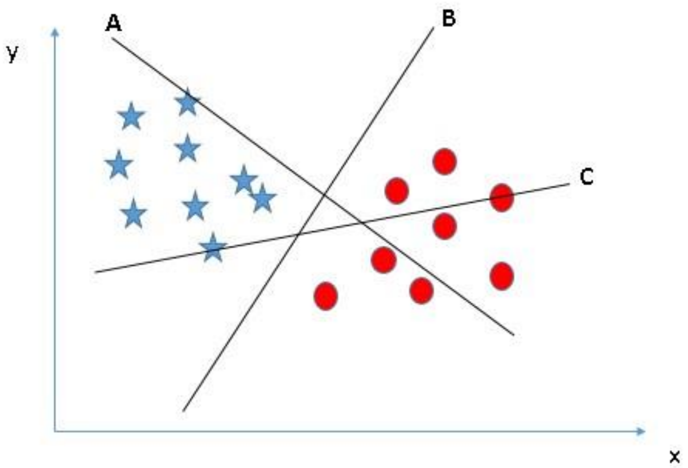



Figure3: Scenario-1

You need to remember a thumb rule to identify the right hyper-plane: "Select the hyper-plane which segregates the two classes better". In this scenario, hyper-plane "B" has excellently performed this job.

5 **Identify the right hyper-plane (Scenario-2):** Here, we have three hyper-planes (A, B and C) and all are segregating the classes well. Now, How can we identify the right hyper-plane?

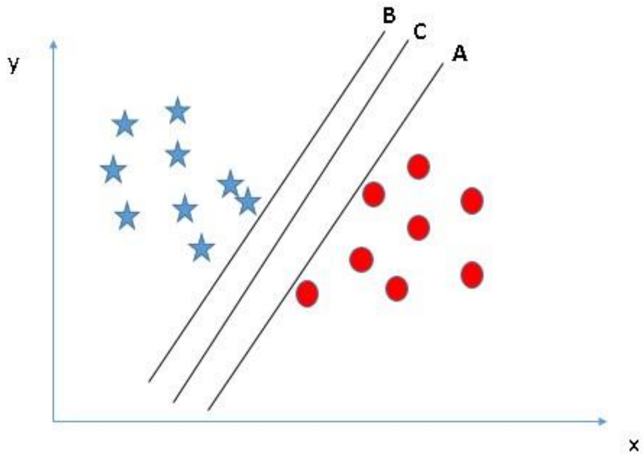
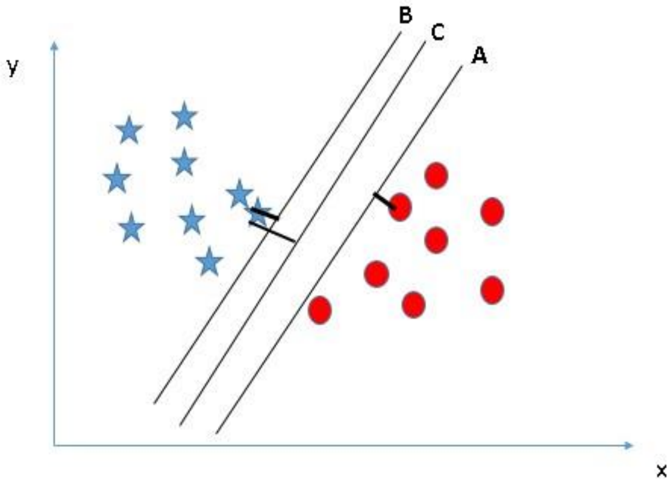



Figure4: Scenario-2

Here, maximizing the distances between nearest data point (either class) and hyper-plane will help us to decide the right hyper-plane. This distance is called as **Margin**. Let's look at the below snapshot:




Above, you can see that the margin for hyper-plane C is high as compared to both A and B. Hence, we name the right hyper-plane as C. Another lightning reason for selecting the hyper-plane with higher margin is robustness. If we select a hyper-plane having low margin then there is high chance of miss-classification.

**6 Identify the right hyper-plane (Scenario-3):** Hint: Use the rules as discussed in previous section to identify the right hyper-plane

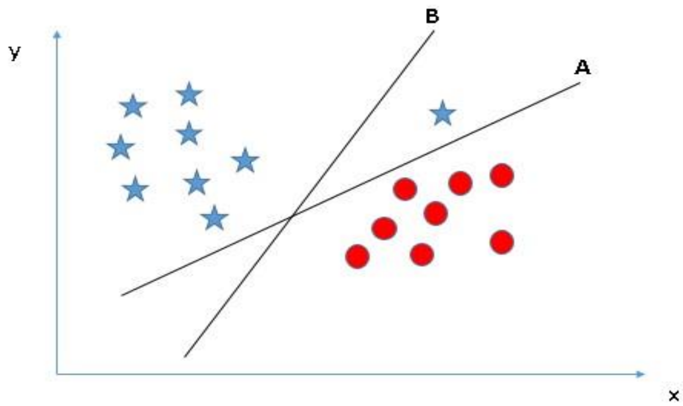



Figure5: Scenario-3

Some of you may have selected the hyper-plane **B** as it has higher margin compared to **A.** But, here is the catch, SVM selects the hyper-plane which classifies the classes accurately prior to maximizing margin. Here, hyper-plane B has a classification error and A has classified all correctly. Therefore, the right hyper-plane is **A.**

7 **Can we classify two classes (Scenario-4)?:** Below, I am unable to segregate the two classes using a straight line, as one of star lies in the territory of other(circle) class as an outlier.

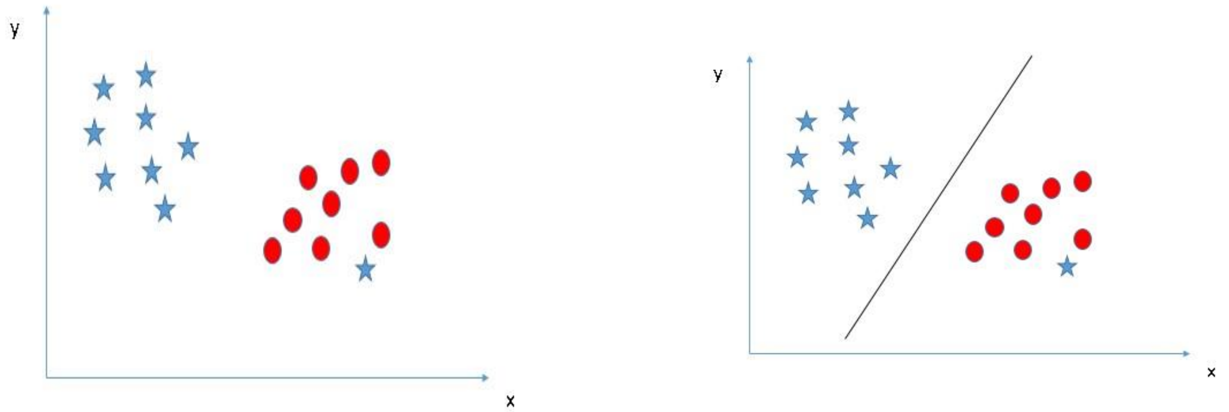



Figure6: Scenario-4

As I have already mentioned, one star at other end is like an outlier for star class. SVM has a feature to ignore outliers and find the hyper-plane that has maximum margin. Hence, we can say, SVM is robust to outliers.

8 **Find the hyper-plane to segregate to classes (Scenario-5):** In the scenario below, we can't have linear hyper-plane between the two classes, so how does SVM classify these two classes? Till now, we have only looked at the linear hyper-plane.


Figure7: Scenario-5

SVM can solve this problem. Easily! It solves this problem by introducing additional feature. Here, we will add a new feature z=x^2+y^2. Now, let's plot the data points on axis x and z:

In above plot, points to consider are:

**9** All values for z would be positive always because z is the squared sum of both x and y

**10** In the original plot, red circles appear close to the origin of x and y axes, leading to lower value of z and star relatively away from the origin result to higher value of z.

In SVM, it is easy to have a linear hyper-plane between these two classes. But, another burning question which arises is, should we need to add this feature manually to have a hyper-plane. No, SVM has a technique called the kernel trick. These are functions which takes low dimensional input space and transform it to a higher dimensional space i.e. it converts not separable problem to separable problem, these functions are called kernels. It is mostly useful in non-linear separation problem. Simply put, it does some extremely complex data transformations, then find out the process to separate the data based on the labels or outputs you've defined.

**11** It works really well with clear margin of separation ➢ It is effective in high dimensional spaces.

**12** It is effective in cases where number of dimensions is greater than the number of samples.

**13** It uses a subset of training points in the decision function (called support vectors), so it is also memory efficient.

## II. METHODOLOGY

In order to monitor the affected level of DR condition a grading classification algorithm is necessary. A set of standard graded fundus images are collected from ophthalmologist which are graded according to the level of retinopathy condition. It spans into four classes no DR condition or normal, mild DR, moderate DR and severe DR. The ability to detect abnormalities in fundus images due to DR leads to the formulation of a system which can generate diagnosis without human interventions. The automatic screening system is trained to classify the fundus images similar to the classified image as that of ophthalmologist. In a real time environment there are many aspects which affects the grading of the image and results in error output. For this reason a pre-processing step is performed for correct diagnosis. The pre-processing step comprises of green channel extraction, image enhancement by adjusting the contrast value, vessel central light reflex removal, background homogenization and vessel enhancement for vessel segmentation. The second step is to apply entropy filter followed by removal of the optic disc and blood vessels in order to segment exudate. The texture features of Grey Level Cooccurrence Matrix (GLCM) are extracted from the segmented image. The classifiers like Support Vector Machine (SVM), multilayer network Scaled Conjugate Gradient – Back Propagation Network (SCG-BPN) and Generalized Regression Network (GRN), Probabilistic Neural Network (PNN), Radial Basis Network (RBF) are tested. It is found that SVM classifier is more accurate and exhibit high performance. The classifier classifies the fundus images as normal, mild, moderate and severe. The images and the severity of DR are transferred to the physician by mail which can be viewed in his mobile phone. The algorithm is tested at a remote location of 25Km away from the Aravind Eye Hospital, Coimbatore and the results are viewed by the vitro surgeon through his mobile phone. The fig.1 shows the methodology in a flow diagram.

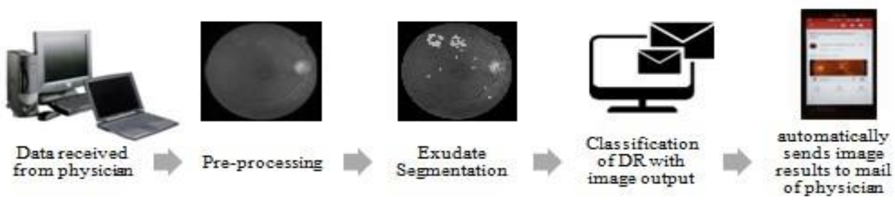



Figure6: methodology of retina dr

### 4.1 Retina Imaging Techniques

An eye fundus image is taken by a “fundus camera”, which is a specialized microscope with an attached camera. A typical fundus camera views 30 to 50 degrees of retinal area, with a magnification of 2:5 [4]. The observation light goes through a series of lenses, and enters the eye through the cornea onto the retina. The reflected light from the retina goes back to the microscope and the camera captures the image immediately. An example of fundus camera is shown in Fig. 3. Blood vessels come into the retina through the optic disc. This point is also known as the blind spot, because it doesn't contain photoreceptor cells. In eye fundus images, the optic disc appears as a white ellipse. In the direction from optic disc to the temple is the fovea. This is the more light sensitive area in the eye. The macula contains no vessels, and appears generally as a dark region. Optic disc and macula are two reference points in fundus images. Their position reveals basic information, for example, the left or right eye. Given the limited angle of fundus cameras, only a part of the retina is captured in each image. The diagnosis protocol of diabetic retinopathy states that the diagnosis should include at least two fundus images of 45° per eye, one macula centred, and another optic disc centred.


Figure7: Colour digital fundus camera

Apart from colour digital fundus cameras, Abramoff et al. [5] add the following imaging modalities to a broader category of fundus imaging:

- **Stereo fundus photography:** at the same time two or more view angles of the fundus are acquired by this instrument. This allows the perception of the depth by the ophthalmologist.
- **Hyperspectral imaging:** it is a fundus camera that does not employ the visible light only, but can select specific wavelength bands. This allows particular applications such as oximetry, the quantification of oxygen levels in the bloodstream.
- **Fluorescein Angiography (FA):** is a fundus image of the photons emitted by a contrast agent injected in the patient's blood stream. Fluorescein or indocyanine green fluorophore are the agents typically used.
- **Scanning Laser Ophthalmoscope (SLO):** An instrument that uses low powered lasers to image the retina or choroid. It uses a very narrow moving beam of light which can bypass most ocular media opacities (i.e. corneal scars, cataracts, vitreous haemorrhage) to reach the surface of the retina and record its surface detail. With SLO, the optics of the eye serves as the objective lens. Confocal SLO is SLO equipped with a confocal aperture. Adaptive optics SLO optically corrects the laser reflections by modelling the aberrations in its wave front.

The other imaging technique that is becoming increasingly important is Optical Coherence Tomography (OCT). OCT is a non-destructive imaging technique that uses interferometry techniques to measure the time of flight of the light backscattering through the retina. By rapidly scanning the eye, it can acquire an in vivo representation of the anatomic layers within the retina. Because of that it can be used to diagnose diseases such as DME, AMD and Glaucoma with generally a greater precision than with a simple fundus image [6]. Fig. 2.4 shows an example of a "retina slice" that can be acquired with these instruments. However, DR cannot be directly diagnosed because the vessels and many other key features of the retina are invisible in this modality (even if it is possible to algorithmically infer the location of the vasculature by employing the visible shadows as shown by Niemeijer et al. [7]. Other drawbacks of this modality are: the steeper learning curve to use the instrument than a colour fundus camera, the greater acquisition time required to acquire a Field Of View (FOV) comparable to a fundus camera and the substantially higher cost.

### 4.2 Abnormalities Due To DR

DR is one of the top five causes leading to blindness, and is the first cause of blindness for people less than 50 years old [8]. It is a complication of diabetes with a very complex pathogenesis. Most of the time, it has no early warning signs. Diabetic patients are required to undergo regular eye screening. During the screening process digital retinal images are captured by trained individuals. This can be a very time consuming and costly task. This grading system for DR would be quicker, thus allowing patients to receive results as soon as possible hence minimising anxiety and also ensuring referrals to the hospital eye service. Another benefit arises from the fact that human graders are subjective and can also become fatigued, whereas an automated system would provide consistent objective results.

The stages of DR are the early stage and the advanced stage, the early stage which is also known as NonProliferative diabetic retinopathy (NPDR), the capillaries develop tiny dot-like outpouchings called microaneurysms, while the retinal veins become dilated, tortuous, and associated with multiple hemorrhages and intraretinal exudates. In the advanced stage, also known as Proliferative diabetic retinopathy (PDR), retinal ischemia eventually stimulates the formation of fragile new vessels. New vessels can cause the vitreous to separate from retina. If the vessels bleed, a massive hemorrhage may cause sudden visual loss.

The detection and diagnosis of diabetic retinopathy in the early stage can help to tremendously slow the degeneration. At this stage of the disease, lesions such as microaneurysms and hemorrhages are likely to be present. Thus an automatic detection of these lesions can help to make the diagnosis of diabetic retinopathy easier, better and more reliable. Three main lesions are concerned in this work, and presented in the following:

- **Microaneurysms:** dilations of the venous end of retinal capillaries, of variable size, mostly between 10 and 100µm, but not above 125µm. In color retinal images, they appear like little dark red dots (or dark dots in the green channel) detached from blood vessels. They are the first sign of diabetic retinopathy as in fig.4 (a).

- **Hemorrhages:** blood leaks within the retina. They can appear anywhere in the retina, with any size and shape. There are many kinds of haemorrhages such as dot haemorrhages, blot haemorrhages, flame haemorrhages. In color retinal images, haemorrhages appear like dark red regions. The smallest haemorrhages are very similar to microaneurysms as in fig.4 (b).

- **Exudates:** accumulations of lipidic deposits within the retina. They appear yellow in colour retinal images (or as bright regions in the green channel) as in fig.4 (c).

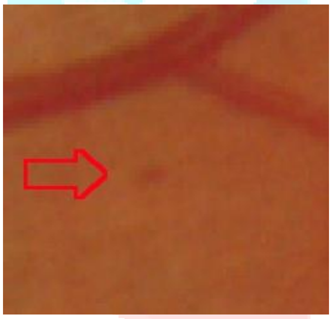


Fig.4.2(a) Microaneurysm

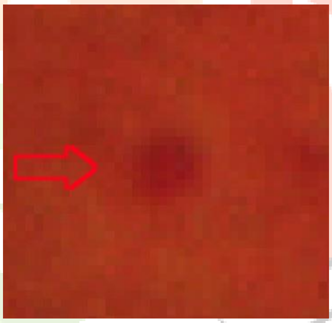


Fig.4.2(b) Hemorrhage

Fig.4.2(c) Exudate

## III. TESTING & IMPLEMENTATION

### 5.1 Test Plan

Before going for testing, first we have to decide upon the type of testing to be carried out. The following factors are taken into consideration:

- To ensure that information properly flows into and out of program
- To find out whether the local data structures maintains its integrity during all steps in an algorithm execution
- To ensure that the module operate properly at boundaries established to limit or restrict processing
- To find out whether error - handling paths are working correctly or not
- To find out whether the values are correctly updated or not
- Check for validations

5.2 General

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product. It provides a way to check the functionality of components, sub assemblies, assemblies and/or a finished product It is the process of exercising software with the intent of ensuring that the Software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of test. Each test type addresses a specific testing requirement.

5.3 Developing Methodologies

The test process is initiated by developing a comprehensive plan to test the general functionality and special features on a variety of platform combinations. Strict quality control procedures are used. The process verifies that the application meets the requirements specified in the system requirements document and is bug free. The following are the considerations used to develop the framework from developing the testing methodologies.

## 5.4 Types of Tests

### 5.4.1 Unit testing

Unit testing involves the design of test cases that validate that the internal program logic is functioning properly, and that program input produce and valid outputs. All decision branches and internal code flow should be validated. It is the testing of individual software units of the application it is done after the completion of an individual unit before integration. This is a structural testing, that relies on knowledge of its construction and is invasive. Unit tests perform basic tests at component level and test a specific business process, application, and/or system configuration. Unit tests ensure that each unique path of a business process performs accurately to the documented specifications and contains clearly defined inputs and expected results.

### 5.4.2 Functional test

Functional tests provide systematic demonstrations that functions tested are available as specified by the business and technical requirements, system documentation, and user manuals. Functional testing is centered on the following items:

Valid Input: Identified classes of valid input must be accepted.

Invalid Input: Identified classes of invalid input must be rejected.

Functions: Identified functions must be exercised.

Output: Identified classes of application outputs must be exercised.

Systems/Procedures: interfacing systems or procedures must be invoked.

### 5.4.3 System Test

System testing ensures that the entire integrated software system meets requirements. It tests a configuration to ensure known and predictable results. An example of system testing is the configuration Oriented system integration test. System testing is based on process descriptions and flows, emphasizing pre-driven process links and integration points.

### 5.4.4 Performance Test

The Performance test ensures that the output be produced within the time limits, and the time taken by the system for compiling, giving response to the users and request being send to the system for to retrieve the results.

### 5.4.5 Integration Testing

Software integration testing is the incremental integration testing of two or more integrated software components on a single platform to produce failures caused by interface defects. The task of the integration test is to check that components or software applications, e.g. components in a software system or – one step up – software applications at the company level – interact without error.

### 5.4.6 Acceptance Testing

User Acceptance Testing is a critical phase of any project and requires significant participation by the end user. It also ensures that the system meets the functional requirements.

Acceptance testing for Data Synchronization:

- The Acknowledgements will be received by the Sender Node after the Packets are received by the Destination Node.
- The Route add operation is done only when there is a Route request in need.
- The Status of Nodes information is done automatically in the Cache Updation process.

### 5.4.7 Black Box Testing

It is a software testing approach in the the tester doesn't know the internal working of the item being tested. For example in a Black box test, on software design the tester only knows the input and the expected outputs. Tester doesn't know how the program derives the output. Tester doesn't even imagine as to how, the coding is done. Tester need to know only the specifications.

- The advantages of black box testing approach are test is unbiased because the designer and the tester is independent of each other
- The tester needs no specific knowledge on any programming language.
- The test is done from the point of view of the user, not the designer.
- The test can be designed as soon as the specifications are complete
- The disadvantages of black box testing approach are
- The test can be redundant if the software designer has already run a test case.
- The test can be difficult to design
- Testing every possible input stream is unrealistic.

### 5.4.8 TEST CASE

| TEST ID | TEST DESCRIPTION | TEST STEPS | EXPECTED OUTPUT | ACTUAL OUT PUT | STATUS |
|---|---|---|---|---|---|
| TC-01 | Accept of retina image through gallery. | Input retina image through gallery | Should accept the image through gallery | Accepted retina image through gallery | Success |
| TC-02 | Acceptance of retina image through picture. | Input retina image through picture. | Should accept the image through picture. | Accepted retina image through picture. | Success |
| TC-03 | Non –acceptance of image other than retina through gallery. | Input image other than retina through gallery. | Should not accept the image other than retina through gallery. | Not-accepted image other than retina through gallery. | Success |
| TC-04 | Accept of retina image through photo. | Input retina image through photo. | Should accept the image through photo. | Accepted retina image through photo. | Success. |
| TC-05 | Non-acceptance of image other than retina through pictures. | Input retina image through pictures. | Should not accept the image other than retina through pictures. | Not-accepted image other than retina through pictures. | Success. |

| | | | | | |
|---|---|---|---|---|---|
| TC-06 | Not-accepted image other than retina through photo. | Input retina image through photo. | Should not accept the image other than retina through photo. | Not-accepted image other than retina through photo. | Success. |
| TC-07 | Acceptance of change in image. | Input image necessary to change. | Should accept the necessary change in image. | Accepted the necessary change in image. | Success. |
| TC-08 | Acceptance of retina image. | Input retina image. | Should accept the retina image. | Accepted the retina image. | Success. |
| TC-09 | Non-acceptance of image other than retina | Input image other than retina | Should not accept images other than retina. | Not- accepted image other than retina | Success. |
| TC-10 | Displaying the Severity level. | Input retina image. | Should Display Severity Level. | Displayed Severity Level. | Success. |

**5.5 SYSTEM IMPLEMENTATION**

System implementation is the important stage of app when the theoretical design is tunes into practical system. The main stages in the implementation are as follows:

- Planning
- Training
- System testing and
- Changeover planning

Planning is the first task in the app implementation. Planning is deciding on the method and the time scale to be adapted. At the time of implementation of any system people from different departments and system analysis involve. They are confirmed to practical problem of controlling various activities of people outside their own data processing departments. The line manager controlled through an implementation co-ordinate committee. The committee consists of ideas, Problems and complaints of user department. It must also consider,

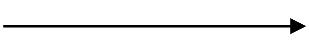
- The implementation of system environment.
- Self selection and allocation for implementation tasks.
- Consultation with unions and resources available.

## SYSTEM FLOW DIAGRAM:

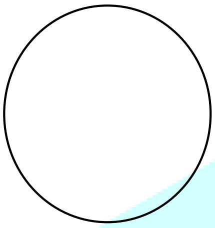
A Data Flow Diagram (DFD) is a diagram that describes the flow of data and the processes that change data throughout a system. It's a structured analysis and design tool that can be used for flowcharting in place of or in association with information. Oriented and process oriented system flowcharts. Four basic symbols are used to construct data flow diagrams. They are symbols that represent data source, data flows, and data transformations and Entity relationship. The points at the data are transformed are represented by enclosed figures, usually circles, the are called nodes.

**8.1.1 SYSTEM FLOW DIAGRAM SYMBOLS:**

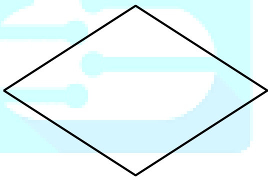
- Source or Destination of System



- System Flow

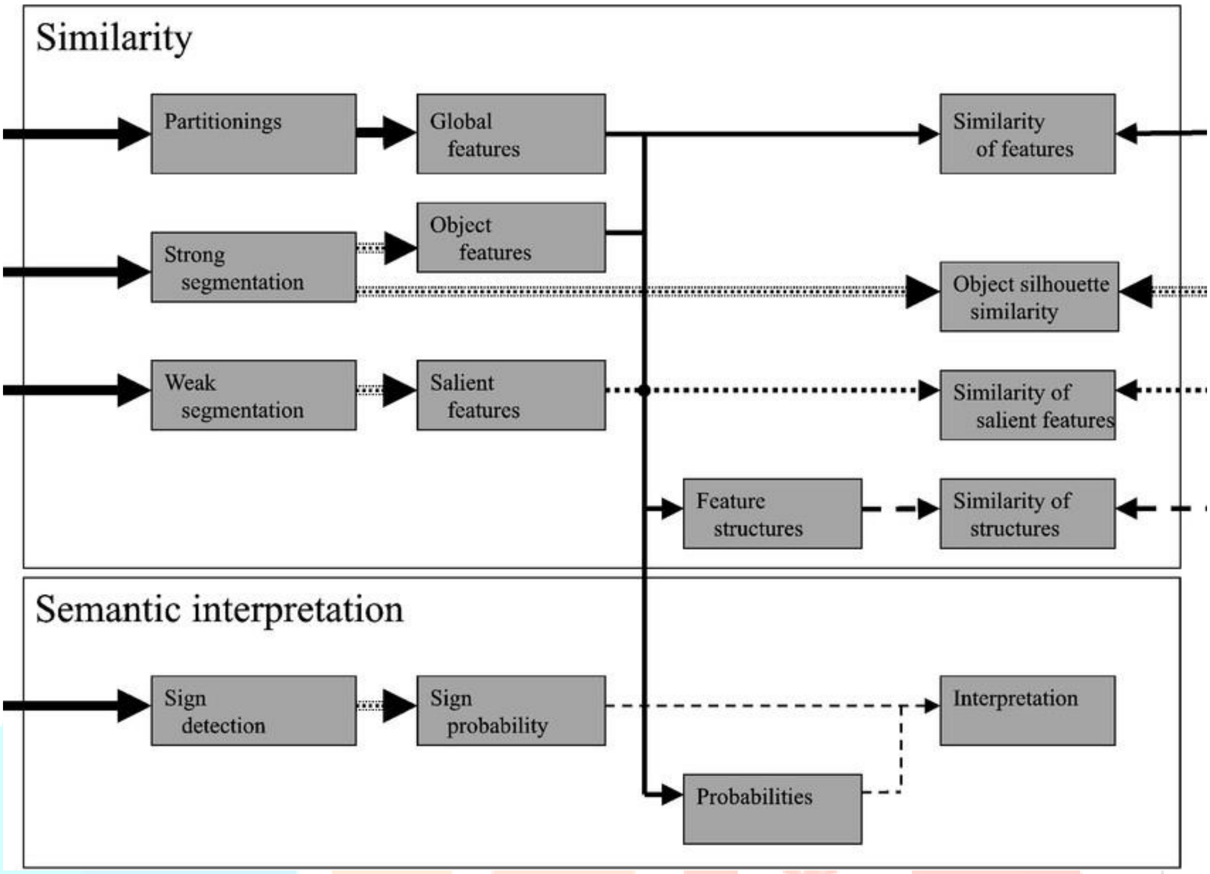


- Process

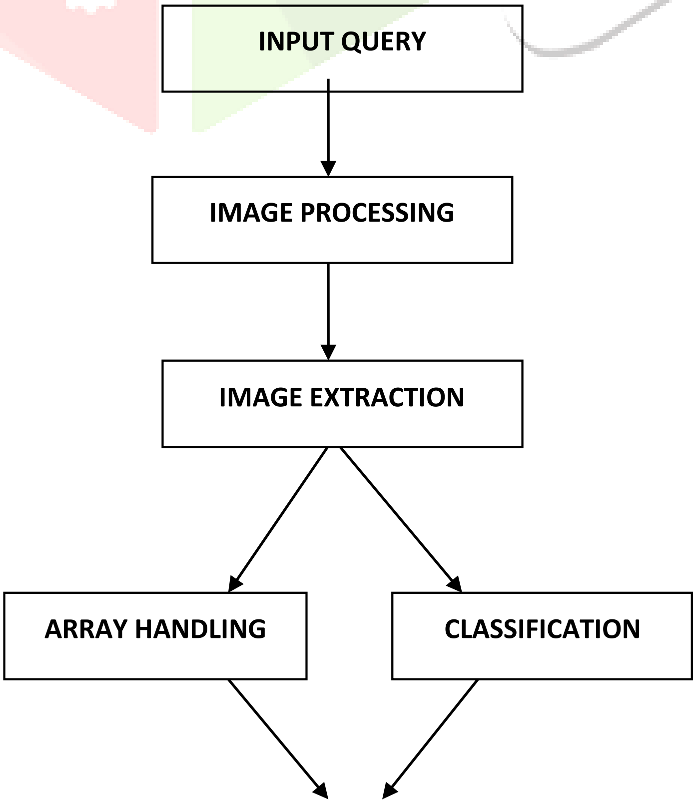


- Entity Relationship

### 8.1.2 SYSTEM FLOW DIAGRAM:



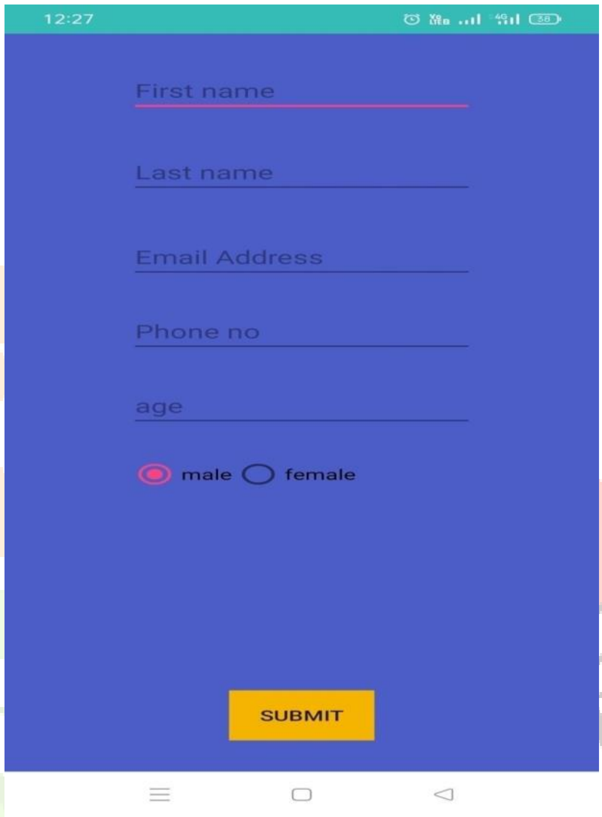

### 8.1.3 SEQUENCE DIAGRAM:

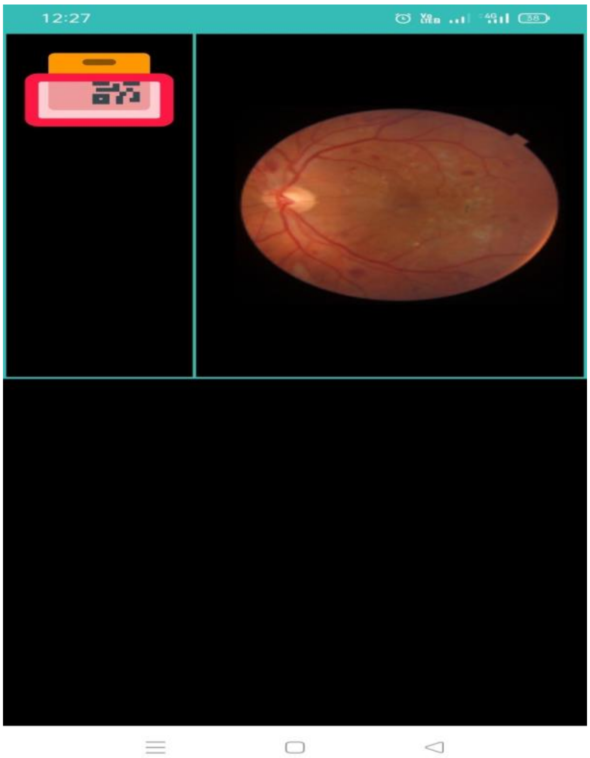


REPORT GENERATION

COMPARISION

**RESULTS AND DISCUSSION**

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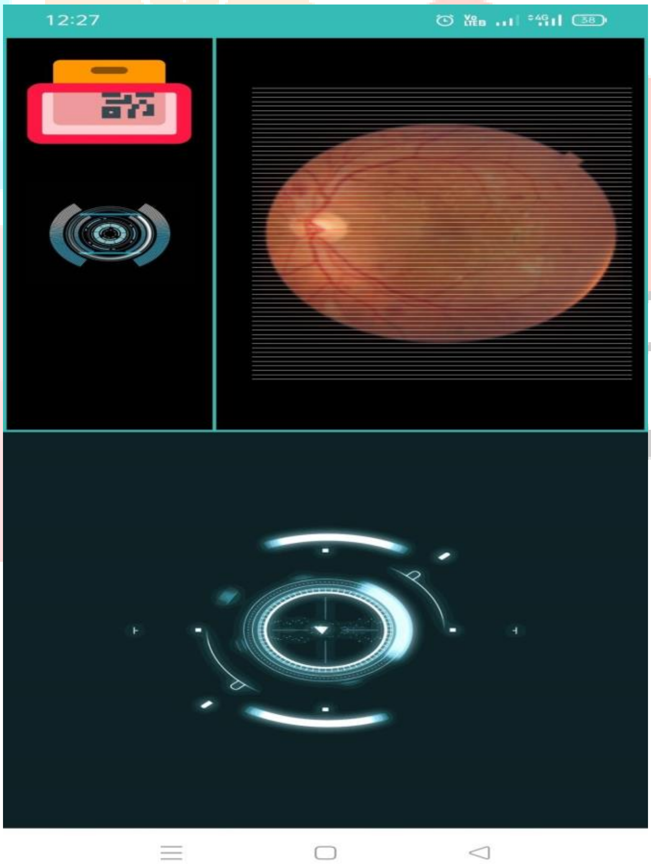
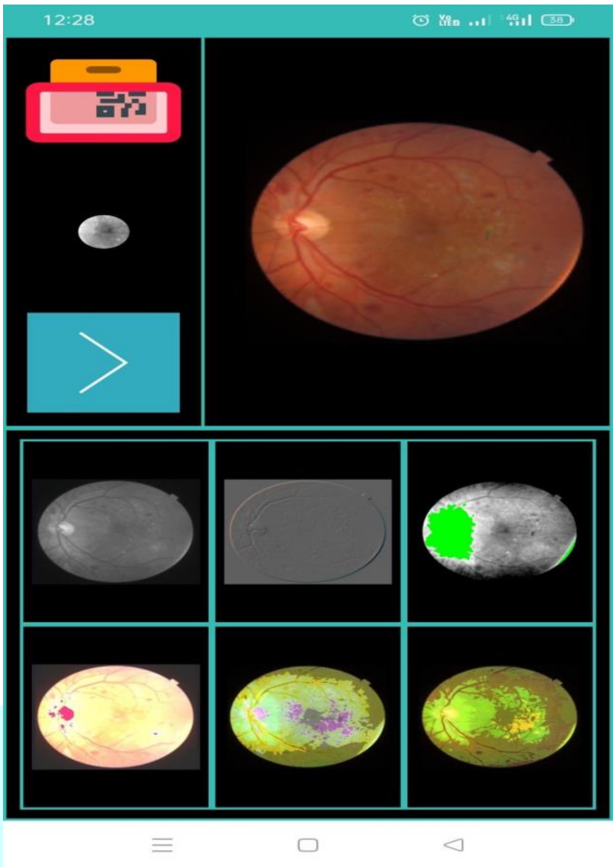

12:27




## CONCLUSION

Early detection of DR can be effective in preventing blindness. The proposed approach is designed for the detection of exudates to diagnose DR. The entropy based segmentation method segments the exudates precisely and clearly. The SVM classifier gives better accuracy and performance compared to SCG-BPN, GRN, PNN, and RBF. This automated system can filter out the exudate images and thereby reduces the burden on ophthalmologist in classifying the exudate images manually. It further classifies the given input image as normal, mild DR, moderate DR and severe DR. This provides the patients to get treated according to their severity level.

The results are also sent to the physician's e-mail which can be viewed by him in his desktop or mobile phone.

This work mainly reduces the time consumption needed for the diagnosis of mass screening processes.

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