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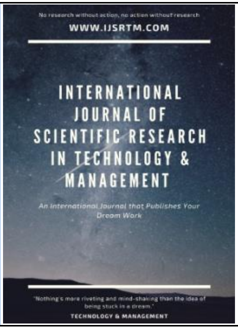

Automatic Diabetic Retinopathy Disease Diagnosis from Fundus Imaging: A Review

Mohini Rathore
Electronics & Communication Engineering
Maulana Azad National Institute of Technology
Bhopal, Madhya Pradesh, India
mohinirathore404@gmail.com

Madhu Shandilya
Electronics & Communication Engineering
Maulana Azad National Institute of Technology
Bhopal, Madhya Pradesh, India
madhu_shandilya@yahoo.in

***Abstract*— In recent decades, there are many cases can be observed which have been affected by Diabetes. This is the most common disease that can be found in people. If a person having this disease from a long time then that person may also suffer from Diabetic Retinopathy; due to that a person may lost his vision partially or completely as per the condition of the retina or how much tissues have been damaged. Diabetic Retinopathy is a disease that cannot be cured and there is no treatment to repair the retina or vision optics. It only can be prevented by taking care of it with routine checkup from medical professionals. It blocks the blood flow towards retina, due to that; blood vessels get swell and exudates started leaking that may cause partial or complete blindness. The intension of this paper is to review various researches which have been done in the field of diabetic retinopathy. Diabetic retinopathy can be automatically diagnosed through fundus imaging and there are many approaches have been made for pertaining better level of accuracy with minimal error rate. System compares machine learning approaches, classifiers and edge detection techniques that have been used for implementing Automatic Diabetic Retinopathy Disease Diagnosis.**

Keywords*— Automatic Diabetic Retinopathy Diagnosis, Fundus Imaging, Optic Disc, Optic Cup, CNN, Retinal Image, Hemorrhages.

I. Introduction

Diabetic retinopathy is a situation that can directly affect the eyes that causes vision loss and visual deficiency in individuals who have diabetes. It influences eyes tissues and blood vessels of the retina. In the situation where a person has diabetes, it's imperative to get an exhaustive eye test; one time a year. This disease may not have any kind of symptoms in the early stage not have any manifestations from the outset — yet thinking that it is early can assist a person with finding a way to secure his vision. The beginning phases of diabetic retinopathy ordinarily don't have any manifestations. Certain individuals change in their vision, similar to inconvenience perusing or seeing distant items. In later phases of the illness, blood vessels in the retina begin to seep into the glassy. Assuming this occurs, it might see hazy, drifting spots or streaks that resemble spider webs. Some of the time, the spots that affected due to light, however it's imperative to seek treatment immediately. Without treatment, the draining can happen severely or deteriorate. Diabetic retinopathy is made by high blood sugar. Over the long haul, having a lot of sugar in your blood can harm the retina, the piece of the eye that distinguishes light and conveys messages to the cerebrum through a nerve toward the rear of the eye (optic nerve). Diabetes harms blood vessels all around the body.

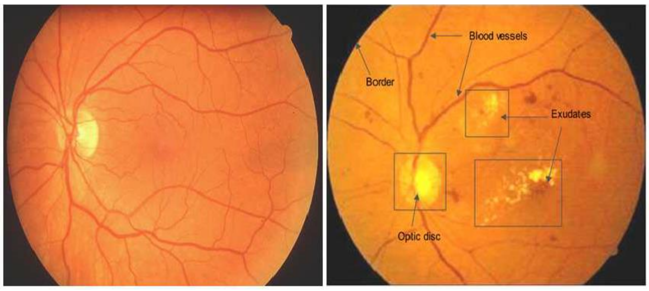

Fig. 1. Impairments over Ratinal Image [2]

The harm to the eyes begins when sugar hinders the minuscule blood vessels that go to your retina, making them release liquid or drain. To compensate for these hindered blood vessels, then it develops fresh blood vessels that don't function admirably. These fresh blood vessels can spill or drain without any problem. These days; computerized image based feature extracting is an immense and demanding region in the field of clinical science for recognizing different illnesses in simple and effective way. Identifying Diabetic retinopathy is a difficult assignment, which is generally dealt with by Ophthalmologist and determination is finished by physically. Physically identification can lead human mistake and results are difficult to duplicate at whatever the point of fundamental diagnosis. The goal of different investigates is to distinguish Diabetic Retinopathy naturally that help ophthalmologists to screen their patients and to do clinical concentrate also which dispose of human blunder and handling time such outcomes can be replicated effectively [1]. The optical structure of the blood vessels or veins over the retinal image can reflect the impairments due the eye related diseases. Most common changes that have been recognized as Vascular, optic circle and fova are utilized to analyze specific eye related diseases, like diabetic retinopathy (DR) and other eye sicknesses. Many screening equipments have been used to identify DR physically. Computerized fundus screening machines are utilized to take pictures of retinal vessels; in this manner, fundus image securing cycle can debase the image quality fairly. So image upgrade is consistently important to further develop the ideal image quality. Specialists recommend a few techniques to work on the nature of retina images. Some image handling techniques utilized by analysts to analyze eye sicknesses, including image improvement, discontinuity, highlight extraction and grouping. Image recording is utilized to identify changes in clinical images. Various images taken from various points are organized in a solitary direction framework for fruitful enlistment. Image combination is utilized to join various sorts of data from various images into a solitary image [1].

Fig. 2. Diabetic Retinopathy vision loss [3]

Image order is utilized to mark the collecting pixels on luminance qualities or different boundaries. Image examination is utilized to effectively comprehend the substance of an image.

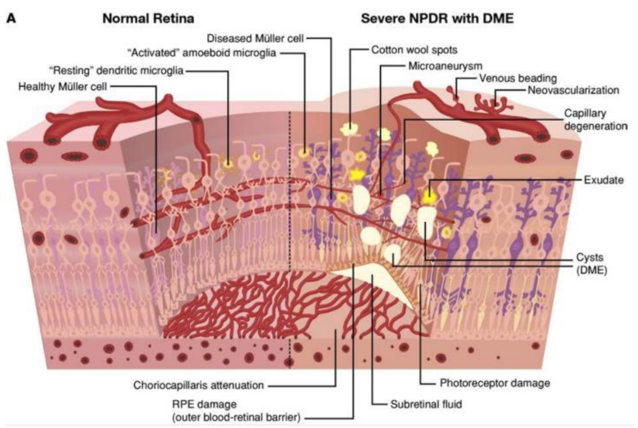

Fig. 3. Normal & NPDR with DME [4]

Diabetic retinopathy frequently has no admonition signs. Indeed, even macular edema, which causes quick vision loss, might not have cautioning signs for some time. In any case, as a general rule, an individual with macular edema is bound to have obscured vision, which is hard to peruse. At times, daytime vision might improve or deteriorate. Patients may not see signs and have 6/6 vision. The best way to distinguish NPDR by immediate or roundabout ophthalmology of a prepared ophthalmologist is to utilize fundus imaging as a true documentation of fundus results, in which micronarism can be seen clearly. Assuming vision is impeded, fluorescein angiography can plainly show that the retinal blood vessels are limited or obstructed (absence of blood stream or retinal ischemia). Macular edema, in which blood vessels and their substance stream into the macular locale, can happen at any phase of NPDR. Highlights obscured vision, mutilated images. Optical lucidness tomography shows spaces of retinal solidifying as liquid aggregates from macular edema. In the subsequent stage, unusual fresh blood vessels (neovascularization) structure behind the eye as a component of diffuse diabetic retinopathy (PDR); these fresh blood vessels are entirely frail, to the point that they can break and cause dying and obscured vision. At the point when this draining first happens, it may not be extremely serious. By arge, it leaves scars of blood or drifting spots on an individual's visual field, albeit the spots regularly vanish following a couple of hours. These scars might drain vigorously over a time of days or weeks, making vision obscured. It can take anyplace from a couple of days to months or a long time to clear within the eye and sometimes the blood may not satisfactory [3].

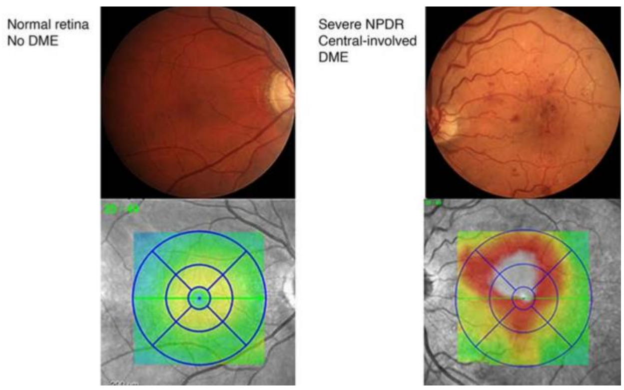

Fig. 4. Fundus Images of Normal & Severe NPDR with DME [4]

On fundoscopic assessment, a doctor will search for cotton fleece stains, aggravation ups (comparative injuries brought about by the alpha-poison of Clostridium torment) and spot blotch dying as per fig 4 that shows the exudates. Albeit the frequency of DR keeps on expanding, the previous ten years has seen the rise of new treatment choices, particularly tranquilizes focusing on VEGF, which have enormously worked on our administration of DME and PDR endpoints. By and by, a squeezing need stays for strong new medicines for all phases of DR, and this supports proceeding with endeavors to completely comprehend the perplexing manners by which diabetes impacts the retina. A significant theoretical development has been the acknowledgment that DR is a sickness of the neurovascular unit, with numerous, associated cell types adding to brokenness of the retina. New helpful methodologies ought to take on this more all encompassing perspective on what diabetes means for the retina and designer proper medicines to all the more exactly characterized illness aggregates with the intriguing possibility of accomplishing fruitful clinical results for all patients [4].

II. RELATED WORKS

A. Related Works

Ravishankar et.al. [5] proposed another strategy to find the optic circle, where they previously distinguished the significant blood vessels and utilized their division to decide the surmised area of the optic plate. Obscured C-Media Clustering tried a few classifiers, including SVM, neural network, PCA and general Bayesian grouping. Alludes to the new control to recognize the optic plate, where the significant blood vessels are found and the inexact situation of the optic circle utilizing their division. It is additionally limited utilizing shading highlights. It shows that many elements, for example, blood vessels, exudates, miniature aneurysms and draining can be precisely related to different transformations that are fittingly applied. Optical circle limitation has a triumph pace of 97.1%, affectability of 95.7% and 95.2% and 90.5% microforma 90.5% microforms separately. These contrast well and existing frameworks and give a genuine model of these frameworks. In this paper blood vessels are extracted using dilation and erosion. Dilation is as follows;

$$A \oplus \mathrm{B} = \mathrm{A}_1(\mathrm{x},\mathrm{y}) = \sup_{i,j\ \in b} \left(A(x-i, y-j) + B(i,j)\right)$$

Erosion is as follows;

$$A \ominus \mathrm{B} = \mathrm{A}_2(\mathrm{x},\mathrm{y}) = \sup_{i,j\ \in b1} \left(A(x-i, y-j) + B_1(i,j)\right)$$

Where B and B_1 are structuring elements and b, b1 are grids.

The combined morphological operation can be stated as;

$$C' = (A \oplus B_2) \ominus B_2 - (A \oplus B_1) \ominus B_1$$

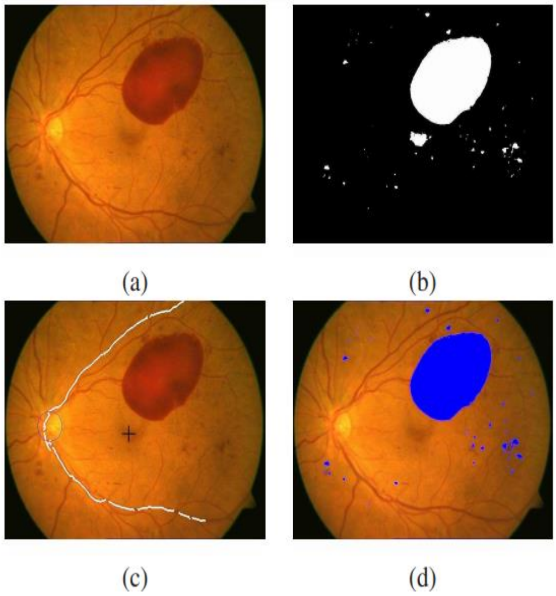

Fig. 5. Illustration of the steps (a) Image dataset, (b) morphological filling, (c) main blood vessel, (d) final result [5]

KK Palavalasa et al. [6] et al. proposed another strategy to recognize hard exudates with high exactness comparative with the degree of injury. In the current strategy, it originally distinguished the exudates sores by using foreground and background technique. Following the subsequent stages, in the last advancement of the calculation, it eliminated the noisy exudates and results accordingly. It has been tried the calculation in the openly accessible DirectDB information base, which contains the essential information. Contrasted with current strategies, it has been accomplished superior execution results for hard exudates sore level discovery with an affectability of 0.87, a F7 score of 0.78 and a positive rating of 0.76. The comparative performance of the system along with certain other researches is shown in the table 1 and resulting parameters have been calculated as; TP is the true positive rate, TN is the true negative rate, FP is the false positive rate and FN is the false negative rate. PPV is the Positive Predict Value and TPR stands for True Positive Rate.

$$TPR = \frac{TP}{TP + FN}$$

$$PPV = \frac{TP}{TP + FP}$$

$$F - Score = \frac{2 * TPR * PPV}{TPR + PPV}$$

Table No. I Result Comparison with Background Subtraction Model

Author	*TPR*	*PPV*	*F-Score*
KK Palavalasa [6]	0.87	0.76	0.78
Sopharak [7]	0.49	0.09	0.16
Walter [8]	0.76	0.59	0.72
Sopharak [9]	0.38	0.10	0.15
Welfer [10]	0.19	0.92	0.31

Alireza et al. [11] proposed a segment dependent on the shading portrayal and its combination with the best color space and Fuse C-Medium (FCM) clustering. They utilized retina shading data for the objectives and showed progress through dim scale based advancements. FCM grouping gave an exactness of 85.6%, an affectability worth of 97.2 and an explicitness of 85.4. In this article the center of the pixel can be changed with small window w and stated as p_n.

$$p_n = 255 * \left(\frac{[\emptyset_w(p) - \emptyset_w(Min)]}{[\emptyset_w(Max) - \emptyset_w(Min)]} \right)$$

Where,

$$\emptyset_w(p) = \left[1 + exp\left(\frac{\mu_w - p}{\sigma_w}\right)\right]^{-1}$$

μ_w σ_w are the mean and standard deviation of the system and Min and Max are the minimum and the maximum value of the window.

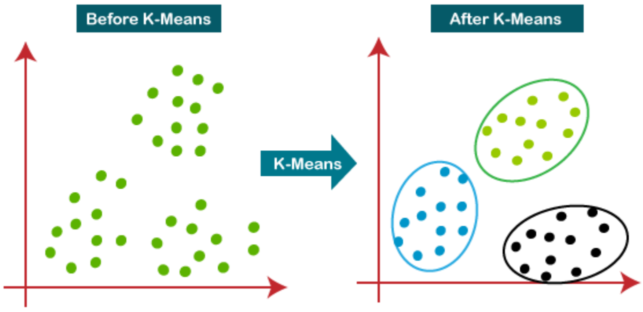

Fig. 6. K-means clustering principle [11]

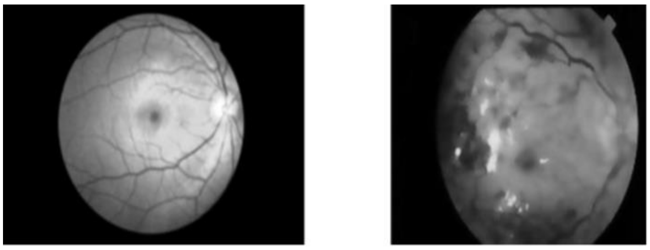

Fig. 7. Segmentation implementation [11]

GG Gardener et al. [12] utilized a back propagation mainstream. Exudates region, vascular region, edema and microanurism region were chosen for distinguishing the disease stages. It can be finished by analyzing images of hundred and 47 patients with DR and thirty ordinary retinal images with exudates, retinal images with draining or microanurism, retinal images with no blood vessels, and retinal images containing blood vessels. The subsequent explicitness and affectability esteems are 88.4 and 83.5, separately.

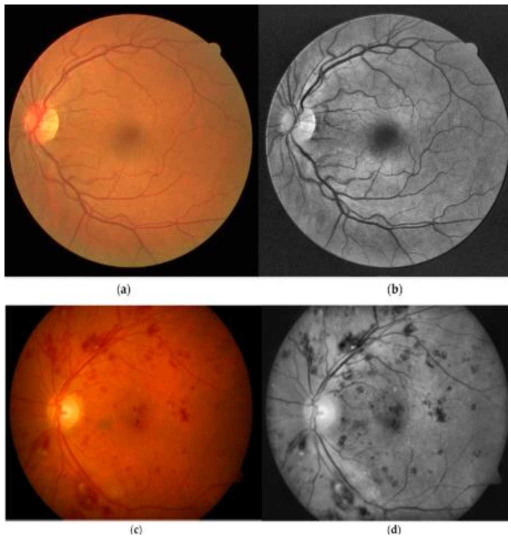

Fig. 8. (a) Original retinal image; (b) Enhancement of image; (c) Original diseased retinal image; (d) Enhancement of image [12]

A. Mukherjee et al. [13] introduced a framework which is based on machine learning to drive the data of 5 classes. There are certain preprocessing techniques are used to improve the data for extracting the features and develop an automated system that can detect the disease with better precision and less damage the retinal information and tried to build a system that can detect the DR at early stage.

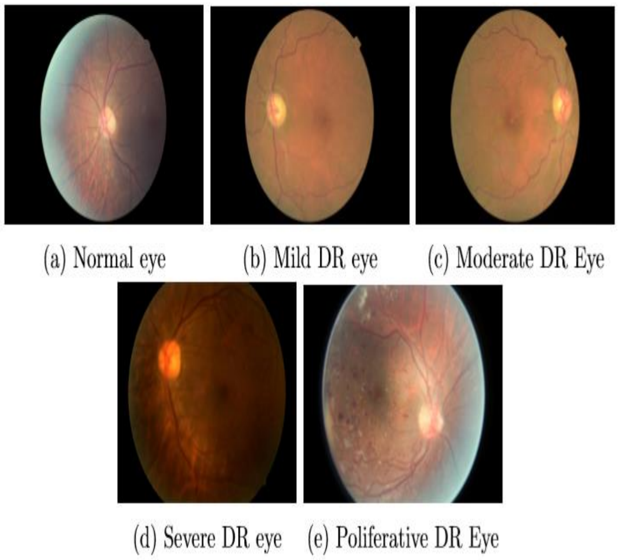

Fig. 9. System Diagnosis Phases [13]

M.W. et al. [14] proposed a framework which is based on various preprocessing techniques and tried to diagnose disease at early stage and reduce the risk of fifty percent of the blindness. There are so many image processing tools through which an image can be enhanced and image can be preprocessed to acquire the effective result and minimize the false alarm rate. But system does not met the desired accuracy and for building the ideal system it is required to attain the better accuracy. Meher Madhu Dharmana et al. [15] proposed an effective and better extraction strategy that is presented to utilizing the image preprocessing and mass location approach on retina images for acquiring fundus features. To accelerate infection recognition of diabetic retinopathy, on a size of 0 to 4.0, the experimentation is acted in the proposed model the diverse characterization calculations are taken care of with the highlights are removed and recognized that Naïve Bayes Classifier is most effective contrasted with different classifiers with a precision of 83%. The proposed work include extraction strategy that has been decreased the existence intricacy when contrasted with the current clustering methods. This strategy can be utilized to assemble an independent reasonable analysis of machine learning approaches by executing it on a minimal expense SOCCs like Raspberry Pi. Feature extraction has been done using Laplacian of Gaussian function.

$$g(x,y,t) = \frac{1}{2\pi t} e^{\frac{-(x^2+y^2)}{2t}}$$

$$L(x,y;t) = g(x,y,t) * f(x,y)$$

$$\nabla^2 L = L_{xx} + L_{yy}$$

Where f(x, y) is the convolutional function that can be operated through Gaussian Kernel Operation. Mamta Arora et al. [16] proposed an execution of ConvNet based calculation for diabetic retinopathy diagnosis from fundus images. This work shows the practicality deep learning way to deal with this issue. There stays a ton of analysis with to keep working on this model. It has been found that the model can be utilized on the highest point of prepared model which can give a considerable lift to the outcomes, however there is a lot better trial that will pertain in future to further develop results.

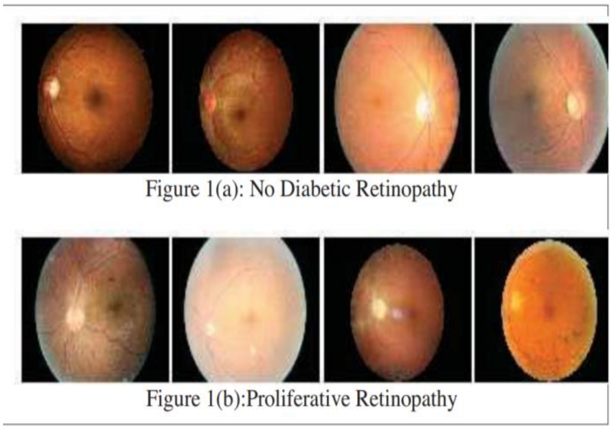

Fig. 10. System Diagnosis Phases [16]

Yash S. Boral et al. [17] proposed a system which is based on deep learning method. System is intended to recognize DR by classifying fundus image. This paper proposed an approach that intended to enhance the quality of an image that increases the efficiency and accuracy of the system. Here the deep network which has been used is name as V3 which is responsible to extract the features of fundus image and try to classify the DR from that. 48 images have been used for training purposed and 90 images are used in testing time. In the last stage of the diagnosis; SVM has been used to classify the disease whether it is diabetic retinopathy or normal image.

III. PROBLEM IDENTIFICATION

KK Palavasala [6] uses background and foreground model for obtaining the result and eroding the noise presented in the images. It directly segmented the image by using binarization method where darker pixels remains available and lighter one get eliminated. It is a very conventional approach where technique deals with black and white pixels, it means that it deals with 0 or 1. But by using this system sensitive information may be eroded and accuracy may directly get affected. In this technique, the old patient data has been stored in database and considered as templates where input data will be compared with these templates and resulted accordingly. Templates are called background fundus image and input data are called foreground fundus images. Later it subtracted with each other and extract the exudates from fundus images and declare the result whether it belongs to DR or not by recognizing extra exudates.

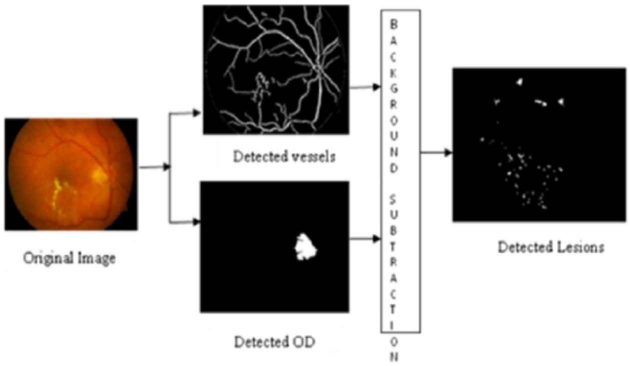

Fig. 11. Background & Foreground Subtraction Model [18]

A significant undertaking in the field of C-Vision and image pre-processing is to identify the foreground and recognize the changes in image clusters. It is a method that attain an image for post data processing and most applications don't need data about the old patients because older data may get differ from the current patient and that could not be consider as the reliable dataset and comparison on the basis of that could lead false result or incorrect recognition. It is just data about changes in the scene, on the foregrounds that the ROI on an image and decision cannot be taken over that. Exudates location is needed after all preprocessing filtrations because these exudates are considered as the impaired cells and system is intended to target these cells. In view of these progressions in the foreground, recognizing the foreground isolates from the background and remain only those pixel where it get differ. It does not work with complex data and those data that pertains new patterns which are totally differ from the templates. It also doesn't work adequately when it contains structural data in the background like blood vessels, veins or nerves that directly affected the accuracy. DR requires the structure of the exudates or impairments that can be pertained through edge detection technique or any other feature extraction methods. Support vector machine is an effective classifier but it can only work effectively when structural data has been pertained. Visually it is possible to classify the exudates from fundus images but deep learning or any other neural network are failed to load all patterns of patient data and classify the new data by comparing with the samples of the datasets.

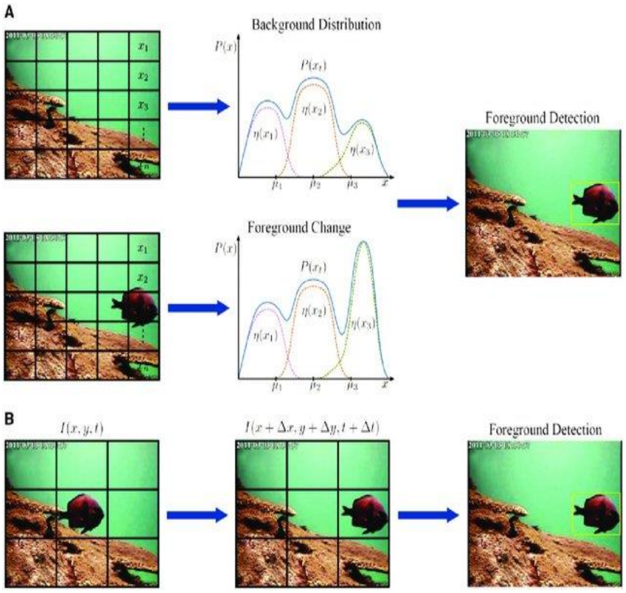

Fig. 12. Segmentation and Erosion using Background & Foreground [19]

Background and foregorund model is subjected to histogam changes in foreground image as compare to the backgound image. If foreground pertains any kind of changes in the histogram of it then it declares the changes detected in which pixel location like Fig. 11 but if there is no changes pertained in the foreground image then it means that the foreground image and background image contain extactly the same pixels. But there is problem with it, if a single pixel get changed then histogram of an image grabbed it and declare the result accorundingly. So that is why it is not effective for dealing with the patient data.

Table No. I Result Comparison of Various Implememted System in Exudates Extraction

Author	*TPR*	*PPV*
Mamta Arora [16]	CNN	74.00
Meher Madhu Dharmana [15]	Blob Detetion	83.00
Pranjali Kokare [20]	Wavelet	86.66
Kranthi K. Palavalasa [6]	Background & Foreground	87.00
Chaudhuri et al.[29]	Template Method	87.73
Jiang and Mojon [30]	Adaptive local thresholding	89.11
Staal et al.[31]	Segmentation Method	94.41
Saumitra Kumar Kuri []	Gabor Filter	97.72

IV. Conclusion & Future Scope

Detecting Diabetic Retinopathy automatically is the solution for routine examination of retina especially for the diabetic patients. It is very important to diagnose this disease on time because it cannot be treated or cured, it can only be prevented or stop to spread over all blood vessels or any kind of cell growth. It can save vision to get partially or completely destroyed due to DR. There are so many researches have been done in the field of DR with there are so many challenges to pertain the better level of accuracy along with less false recognition rate. It is very important to recognize correct outcomes because single false alarm rate may suffer the patient towards complete blindness. There are certain researches which are based on machine learning techniques but system get confused when new pattern of data has been intervened. A research is also based on background and foreground subtraction model which is a conventional approach through which sensitive information can be erode that directly affect the accuracy of the system. So, in future a system can be developed through which a better level of accuracy can be pertained with less false alarm rate and less processing time. System should also be cost effective as well as accurate to diagnose the DR with current patient data.

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