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A Reivew on Automatic Diabetic Retinopathy Disease Diagnosis from Fundus Imaging

Satish Kumar Kushwaha
Dept. of Computer Science & Engineering
SAM College of Engineering & Technology, Bhopal, Madhya Pradesh, India
skkush1994@gmail.com

Neelesh Jain
Dept. of Computer Science & Engineering
SAM College of Engineering & Technology, Bhopal, Madhya Pradesh, India
neeleshcmc@gmail.com

Shekhar Nigam
Dept. of Computer Science & Engineering
SAM College of Engineering & Technology, Bhopal, Madhya Pradesh, India
prof.shekharnigamtnp@gmail.com

***Abstract*— There have been a lot of examples in recent years when diabetes has been a factor. The most prevalent illness affecting individuals is this one. A person who has had this illness for a long period may also develop diabetic retinopathy, which can cause partial or total blindness depending on the health of the retina or the extent of the tissue damage. There is no cure for diabetic retinopathy, and there is no medication that can restore eyesight or the retina. It can only be avoided by taking care of it and getting regular checkups from doctors. It prevents blood from flowing to the retina, which causes blood vessels to enlarge and exudates to start leaking, which can result in partial or total blindness. This paper's goal is to evaluate numerous studies that have been conducted on diabetic retinopathy. Through fundus imaging, diabetic retinopathy may be automatically identified, and several methods have been developed to achieve a higher degree of accuracy with a low error rate. The system compares edge detection methods, classifiers, and machine learning methods that have been applied to automatic diabetic retinopathy disease diagnosis.**

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

I. Introduction

Diabetes patients who have diabetic retinopathy have vision loss and visual impairment due to conditions that can directly impact the eyes. It affects the retinal blood vessels and eye tissues. A thorough eye examination should be scheduled once a year for everyone with diabetes. Even if there may not be any early signs or indications of this disease, believing that it is in its early stages might help a person discover a means to protect his eyesight. Typically, the early stages of diabetic retinopathy don't show any symptoms. Some people have changes in their vision, such as difficulty reading or seeing far-off objects. Blood vessels in the retina start to leak into the eye in the final stages of the sickness. If this happens, it can notice blurry, moving streaks or patches that resemble spider webs. It is important to get treatment right away even if the spots are sometimes caused by light. If left untreated, the drainage may become severe or worsen. High blood sugar causes diabetic retinopathy. The retina, the part of the eye that separates light and sends information to the brain through an optic nerve that runs towards the back of the eye, can become damaged over time if there is a lot of sugar in the blood. Blood vessels all throughout the body are harmed by diabetes. Blood vessels in the retina start to leak into the eye in the final stages of the sickness. If this happens, it can notice blurry, moving streaks or patches that resemble spider webs. It is important to get treatment right away even if the spots are sometimes caused by light. If left untreated, the drainage may become severe or worsen.

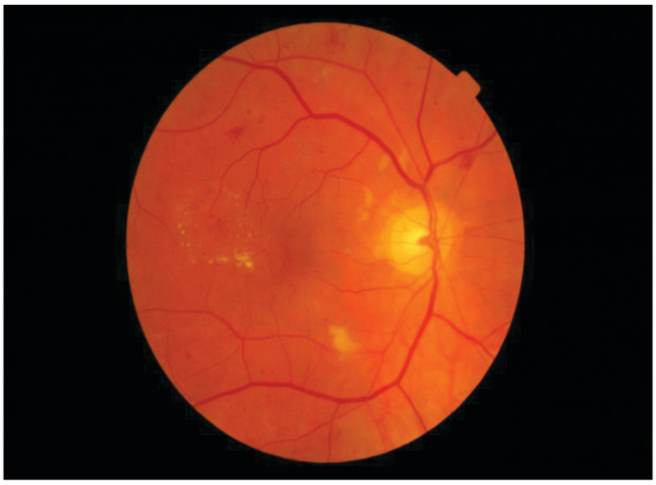

Fig. 1. Impairments over Ratinal Image [2]

High blood sugar causes diabetic retinopathy. The retina, the part of the eye that separates light and sends information to the brain through an optic nerve that runs towards the back of the eye, can become damaged over time if there is a lot of sugar in the blood. Blood vessels all throughout the body are harmed by diabetes. The aim of several studies is to detect diabetic retinopathy naturally, assisting ophthalmologists in patient screening and clinical focus as well as removing human error and managing time such outcomes may be efficiently duplicated [1]. The optical makeup of the veins or blood vessels over the retinal picture might reveal the limitations brought on by disorders of the eye. The most frequent alterations, such as vascular, optic circle, and fova changes, are used to examine particular eye disorders, such as diabetic retinopathy (DR) and other eye illnesses. Physical DR identification has been done using a variety of screening tools. The retinal vessels are photographed using computerised fundus screening devices; as a result, the fundus image securing cycle can significantly degrade the image quality. Therefore, image improvement is always crucial to advancing the optimum image quality. A few methods are suggested by experts to improve the nature of retinal pictures. Image enhancement, discontinuity, highlight extraction, and grouping are some image management techniques that analysts use to examine eye diseases. To spot changes in clinical pictures, image recording is used. For successful recruitment, numerous photos captured from diverse angles are arranged in a single direction framework. Image combining is a technique used to combine different types of data from several photos into a single image [1].

Fig. 2. Diabetic Retinopathy vision loss [3]

To designate the accumulating pixels on luminance quality or other boundaries, image order is used. To efficiently understand a picture's content, one uses image analysis. The warning signals of diabetic retinopathy are usually absent. Even macular edoema, which results in a sudden loss of vision, may take some time to show warning signals. Anyhow, a person with macular edoema is often going to have blurred vision that is challenging to read. Daytime eyesight may occasionally get better or worse. Patients with 6/6 vision may not be able to perceive warnings. Utilising fundus imaging as a real documentation of fundus findings, in which micronarism can be clearly observed, is the best technique to differentiate NPDR by immediate or roundabout ophthalmology of a trained ophthalmologist. If vision is impaired, fluorescein angiography can clearly demonstrate that there are restricted or blocked retinal blood vessels (no blood flow or retinal ischemia). Any stage of NPDR can experience macular edoema, in which blood vessels and their content pour into the macular region. highlights distorted and clouded eyesight. The retinal solidifying gaps are seen as liquid aggregates on optical clarity tomography due to macular edoema. The next stage of diffuse diabetic retinopathy (PDR) is characterised by the formation of unique new blood vessels (neovascularization) behind the eye; these new blood vessels are extremely fragile and have the potential to burst, resulting in blindness and death. When this draining initially starts, it might not be anything that has to be taken seriously. By and large, it leaves traces of blood or drizzling spots in a person's field of vision, though these often go away within a few of hours. These scars may discharge rapidly over the course of a few days or weeks, obstructing vision. The eye can take anything from a few days to months or even longer to clear, and occasionally the blood may not be sufficient [3]. During a fundoscopic examination, a physician will look for exudates (fig. 4), cotton fleece stains, aggravation ups (comparative injuries caused by the alpha-poison of Clostridium discomfort), and spot blotch dying. Although the occurrence of DR has increased over the past 10 years, new therapy options, notably tranquillizers that target VEGF, have significantly improved our management of DME and PDR outcomes.

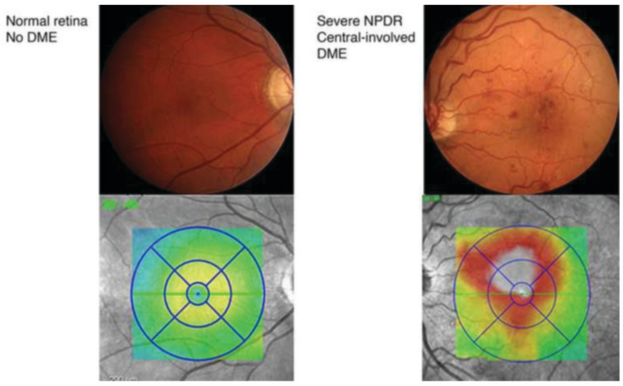

Fig. 3. Fundus Images of Normal & Severe NPDR with DME [4]

Over time, there will continue to be a pressing need for potent novel treatments for all stages of DR, which encourages more research into the myriad ways that diabetes affects the retina. The recognition that DR is a disease of the neurovascular unit with various, linked cell types adding to the retina's damage has been a key theoretical breakthrough. With the intriguing possibility of achieving successful clinical results for all patients, new helpful methodologies should adopt this more comprehensive perspective on what diabetes means for the retina and design appropriate medications to all the more precisely characterized illness aggregates [4].

II. RELATED WORK

A. Related Works

Another method to locate the optic circle was suggested by Ravishankar et al. [5], who had previously identified the important blood veins and used their division to determine the approximate location of the optic plate. Several classifiers were tested by Obscured C-Media Clustering, including SVM, neural network, PCA, and generic Bayesian grouping. refers to the newly developed method of identifying the optic plate, which is home to the important blood arteries and the irregular location of the optic circle caused by their division. Additionally, it is restricted by using shade details. It demonstrates how several components, including blood arteries, exudates, tiny aneurysms, and drainage, may be exactly tied to various changes when they are used appropriately. The victory rate for optical circle limitation is 97.1%, the affectability is 95.7%, 95.2%, and 90.5% microforms individually. These provide a true representation of these frameworks and contrast favourably with existing ones. In this study, dilation and erosion are used to remove blood vessels. Another method was put up by KK Palavalasa et al. [6] et al. to identify hard exudates with good accuracy in relation to the severity of the injury. Using foreground and background techniques, the exudates sores were initially differentiated in the current method. After the succeeding steps, the calculation's last progression deleted the loud exudates and adjusted the findings as necessary. The computation has been tested in the publically available DirectDB information base, which provides the crucial data. With an affectability of 0.87, a F7 score of 0.78, and a positive rating of 0.76, it has proven possible to get higher execution outcomes for hard exudates painful level finding as compared to current tactics. Table 1 compares the system's performance with that of previous studies, and the resulting parameters have been determined as follows: TP stands for true positive rate, TN for true negative rate, FP for false positive rate, and FN for false negative rate. TPR is for True Positive Rate, while PPV stands for Positive Predict Value. A segment based on shading depiction and its fusion with the optimal colour space and Fuse C-Medium (FCM) clustering was proposed by Alireza et al. [11]. They used retina shading data to achieve their goals and demonstrated advances using changes based on a dim scale. An explicitness of 85.4, an affectability worth of 97.2, and an accuracy of 85.6% were provided by the FCM grouping.

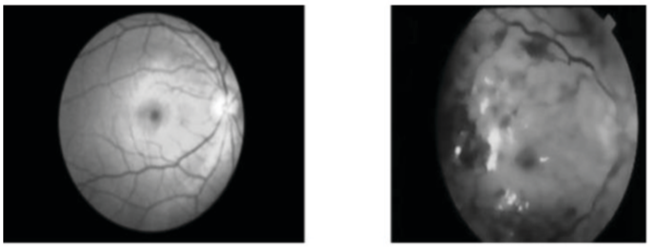

Fig. 4. Segmentation implementation [11]

GG Gardener et al. [12] utilized a back propagation mainstream. For identifying the phases of the disease, the exudates region, vascular region, edoema, and microanurism region were selected.

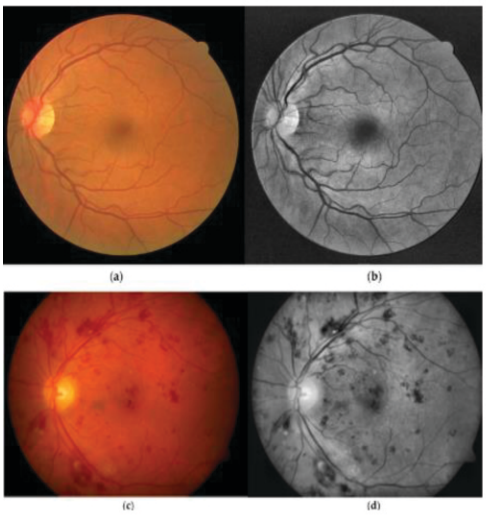

Fig. 5. (a) Original retinal image; (b) Enhancement of image; (c) Original diseased retinal image; (d) Enhancement of image [12]

It may be completed by examining photographs taken of a hundred and forty-seven people with DR as well as thirty photographs of a normal retina with exudates, photographs of a retina with draining or microanuria, photographs of a retina with blood vessels, and photographs of a retina without blood vessels. 88.4 and 83.5, respectively, are the next-best explicitness and affectability ratings. Machine learning-based framework for 5 classes' data was introduced by A. Mukherjee et al. [13]. An automated system that can diagnose the illness with more accuracy and less harm to the retinal information is being developed, and efforts are being made to create a system that can identify DR at an early stage. Various preprocessing approaches are being employed to enhance the data for extracting the characteristics. A framework that is based on several preprocessing approaches was suggested by M.W. et al. [14] in an effort to identify illness at an early stage and lower the chance of blindness by 50%. There are several image processing tools available that may be used to improve and preprocess a picture in order to get the best results and reduce the number of false alarms. However, the system does not achieve the requisite precision, and higher accuracy is needed to develop the perfect system. 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. On a size of 0 to 4.0, the experimentation is carried out in the suggested model, the various characterization calculations are handled with the highlights are removed, and it is discovered that Nave Bayes Classifier is most effective in comparison to other classifiers with a precision of 83%. When compared to the present clustering approaches, the suggested work includes an extraction strategy that has reduced the complexity of the existing situation. By using it on low-cost SOCCs like the Raspberry Pi, this technique may be used to put together an independent, logical critique of machine learning algorithms. Laplacian of the Gaussian function was used for feature extraction. where the convolutional function that may be processed using the Gaussian Kernel Operation is f(x, y). ConvNet-based calculations were proposed by Mamta Arora et al. [16] for the detection of diabetic retinopathy using fundus pictures. This paper demonstrates the applicability of deep learning as a solution to this problem. There is still a lot more study to be done in order to improve this model. It has been discovered that the model can be applied to the best-prepared model scenario, which may significantly improve the results. However, there is much better trial that will apply in the future to further enhance results.

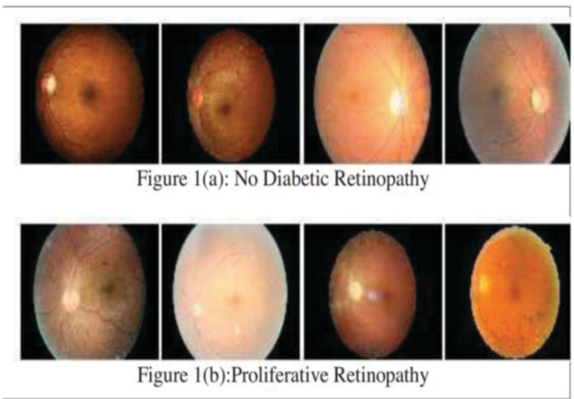

Fig. 6. System Diagnosis Phases [16]

A deep learning-based system was proposed by Yash S. Boral et al. [17]. The system's goal is to categorise the fundus picture and identify DR. This research put out a method for improving picture quality in order to boost the system's effectiveness and precision. This deep network, known as V3, is in charge of extracting the characteristics of the fundus picture and attempting to categorise the DR from it. For training purposes, 48 photographs were used, while 90 images were used for testing. SVM has been utilised in the last step of diagnosis to categorise the condition as either diabetic retinopathy or a normal picture.

III. Problem Identification

The background and foreground model is used by KK Palavasala [6] to reach the result and reduce the noise shown in the photos. By employing the binarization approach, it immediately segmented the image, keeping the darker pixels and removing the brighter ones. It is a fairly traditional method since the technique only works with pixels that are either 0 or 1. However, utilising this technique might directly impact accuracy and erode important information. Old patient data that was kept in a database and used as templates in this approach will be compared to the input data and the results will be determined appropriately. Foreground fundus photos are input data, while background fundus images are templates. Exudates are then extracted from fundus pictures and subtracted from one another. By identifying additional exudates, the outcome is then declared whether it belongs to DR or not.

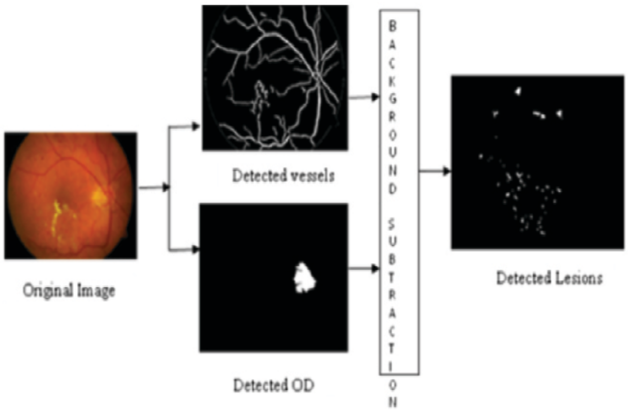

Fig. 7. Background & Foreground Subtraction Model [18]

Identifying the foreground and recognising the changes in picture clusters is an important task in the field of C-Vision and image pre-processing. It is a technique for obtaining an image for post-processing, and the majority of applications do not require information on older patients because this information may differ from that of the current patient and cannot be regarded as a reliable dataset, making comparisons based on it risk producing false results or incorrect recognition. The ROI on a picture is only information about changes in the scene's foregrounds, and no decisions should be made based on it. After completing all pretreatment filtrations, it is necessary to locate exudates since the system is designed to target these exudates as impaired cells. Given these developments in the foreground, it is possible to distinguish the foreground from the background and save just the pixels that vary. Complex data and data pertaining to brand-new patterns that are significantly different from the templates are not supported. Additionally, it is ineffective when background structural information such as blood arteries, veins, or nerves directly affects accuracy. The structure of the exudates or impairments is needed for DR, and this structure may be ascertained using the edge detection approach or any other feature extraction techniques. Although support vector machines are good at classifying data, they only function well when structural data has been considered. Visually, exudates from fundus pictures may be classified, but deep learning or any other neural network is unable to load all patient data patterns and categorise new data by comparing it to samples from existing. When compared to the background image, the foreground and background models are sensitive to historical changes. If the foreground picture has any sort of modifications, the histogram of it will indicate which pixels have changed, as shown in Figure 11, but if there are no changes, the foreground image and background image will have exactly the same pixels. However, there is an issue with it; if just one pixel is modified, the histogram of the image will grasp it and accurately announce the outcome. Because of this, it is ineffective for handling patient data.

TABLE I. Result Comparison

Author	***TPR***	***PPV***
Mamta Arora [16]	CNN	74.00
Meher Madhu [15]	Blob Detetion	83.00
P Kokare [20]	Wavelet	86.66
Kranthi K. P [6]	Background & Foreground	87.00
Chaudhuri et al.[29]	Template Method	87.73
Mojon [30]	Adaptive local thresholding	89.11
Staal et al.[31]	Segmentation Method	94.41
Saumitra K K [32]	Gabor Filter	97.72

IV. Conclusion

The answer to routine retinal examination, especially for diabetic individuals, is to automatically detect diabetic retinopathy. Early diagnosis of this illness is crucial since it cannot be cured or treated; it can only be stopped from spreading to all blood vessels or any form of cell development. Due to DR, it can prevent eyesight from being damaged entirely or partially. In order to get a higher degree of accuracy and a lower false recognition rate, there have been several studies conducted in the field of DR. Correct results must be recognised because even one false alert might lead the patient to become completely blind. While some research relies on machine learning approaches, when a new pattern of data is introduced, the system becomes confused. A study also uses the background and foreground subtraction model, a traditional method that can degrade sensitive data and have an impact on the system's accuracy. Therefore, a system that achieves a higher degree of accuracy with a lower false alarm rate and faster processing time can be created in the future. The system should be accurate and cost-effective in order to diagnose the DR using up-to-date patient data.

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