

Automatic Diabetic Retinopathy Detection By Using Deep Learning

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Abstract— Diabetes mellitus frequently results in diabetic retinopathy (DR), a condition that causes irreversible retinal lesions and increases the risk of blindness if left untreated. Ophthalmologists' manual diagnosis is labor-intensive and error-prone, necessitating computer-aided methods. In the area of DR detection using color fundus images, deep learning—more specifically, convolutional neural networks (CNNs)—has demonstrated encouraging outcomes. Current research has examined and studied cutting-edge techniques for DR classification that make use of deep learning. These methods provide enhanced medical image analysis capabilities, supporting early diagnosis and therapy. But issues like robust algorithms and the availability of datasets still need to be addressed in order to improve the accuracy and dependability of DR diagnosis.

Keywords— Diabetic Retinopathy; Deep Learning; Convolutional Neural Network (CNN); Fundus images; Stages of DR; Ophthalmology.

I. INTRODUCTION

Diabetes is the world's most serious epidemic, particularly in Indian society. As a result, there is an excess of diabetes, which spreads diseases like DR. To increase the workload of the ophthalmic team and decrease patient morbidity, an automated diagnosis model must be created [1]. Diabetes-related retinal degeneration (DR) is a serious condition that can lead to blindness due to damage to the retina's fragile blood vessels. There are four unique stages that this condition proceeds through: proliferative diabetic retinopathy, moderate non-proliferative retinopathy, severe non-proliferative retinopathy, and mild non-proliferative

retinopathy. Every stage has distinct traits that contribute to the diagnostic procedure's complexity, especially in the early stages when there are no warning indications. The fact that prompt treatment and surveillance might potentially reduce future cases of DR by a significant 56% highlights how serious the situation is. Nevertheless, even highly skilled professionals find it difficult to correctly diagnose the illness in its early stages. For early-stage detection, the manual evaluation of diagnostic fundus images is complex, and the inefficiencies of current diagnosis techniques lead to disputes among ophthalmologists and the production of erroneous ground-truth data for scientific investigations. Several strategies have evolved to address the detection of DR in response to these issues. These methods were initially based on conventional computer vision techniques. Nonetheless, deep learning has been more popular recently, as convolutional neural networks (CNNs) have proven their superiority in tasks like object identification and classification, which includes the diagnosis of diabetic retinopathy [2]. NPDR, or non-proliferative diabetic retinopathy, is a primary stage diabetic retinal condition that manifests some of the following symptoms. Microaneurysms (MA) are a typical symptom of diabetic retinopathy (DR). They appear as red patches with sharp margins and smaller than 125µm in size. Hemorrhages (HM) are bigger areas that measure more than 125µm in diameter. Capillary leaks cause two types of hemorrhages: blot hem and superficial hem. Hard exudates, which are caused by plasma leakage, appear as bright yellow spots

with distinct borders in the macular area. Cotton wool spots, also known as soft exudates, are white patches that develop on the retinal tissue as a result of enlarged nerve fibers. The following symptoms are present in Proliferative Diabetic Retinopathy (PDR), an advanced stage of diabetic retinal disease. Neovascularization, or the development of new abnormal vessels at the optic disc or other locations in the retinal region, occurs primarily in PDR, Vitreous hemorrhage - The abnormal retinal vessels may proliferate inside or around the vitreous body. Mild Non-Proliferative Retinopathy: earliest stage of retinopathy due to diabetes defined by the development of microaneurysms. minimal effect on blood vessels, with little to no distortion [3].



Fig. 1. Different stages of Diabetic Retinopathy [3]

WHO states that DR is a serious eye condition that has to be urgently considered on a global scale. A survey states that there are roughly 12,000 ophthalmologists in India for every 60 million diabetics who have eye disorders [5].

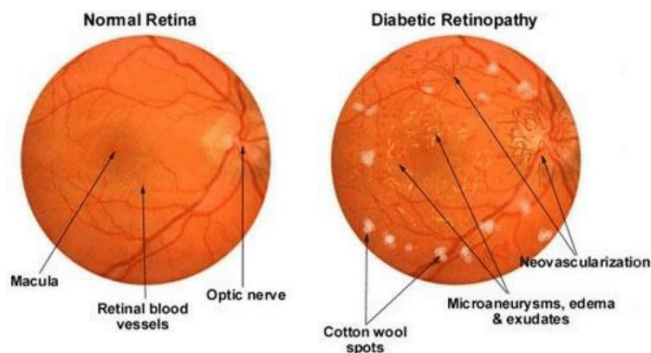


Fig. 2. Impairments over Ratinal Image [21]

The structure of the blood vessels in the retina of the eye provides information about the changes that occur after these retinal related eye diseases. Vascular, fova and optic disc (OD) are used to diagnose certain eye symptoms, such as diabetic retinopathy (DR) and other eye diseases. Many screening tools can be accessed to determine DR manually. According to clinical reports, more than ten percent of patients with diabetes have an increased risk of eye problems. Diabetic retinopathy (DR) is an eye disease that has been affecting eighty to eighty-five percent of diabetics for more than ten years. Retinal fundus images are commonly used in clinics to diagnose and diagnose diabetic retinopathy. Raw Retina Funds images are very difficult to process using a machine learning algorithm. In this paper, raw channel funding pre-processes images using color channel extraction, edge detection, image strengthening and resizing techniques. Experiments are performed using the Sobel edge detection technique for Diabetic Retinopathy

Dataset and the results are evaluated based on the true positive, false positive, true negative and false negative for the collected symptoms[21]. The structure of the blood vessels in the retina of the eye provides information about the changes that occur after these retinal related eye diseases. Vascular, fova and optic disc (OD) are used to diagnose certain eye symptoms, such as diabetic retinopathy (DR) and other eye diseases. Many screening tools can be accessed to determine DR manually. Digital fundus cameras are used to take pictures of retinal vessels; Therefore, unwanted brightness, environment and fundus image acquisition process can degrade the image quality somewhat. So image enhancement is always necessary to improve the desired image quality. Researchers suggest some methods to improve the quality of retina images. Some image processing methods used by researchers to diagnose eye diseases, including image enhancement, fragmentation, feature extraction and classification. Image recording is used to detect changes in medical images. Different images taken from different angles are arranged in a single coordinate system for successful registration. Image fusion is used to combine different types of information from different images into a single image. Separation is used to divide an image into multiple areas based on color, intensity, and objects. Image classification is used to label a group of pixels based on gray values or other parameters. Image analysis is used to easily understand the content of an image.

II. RELATED WORKS

A. Related Works

KK Palavalasa et al. proposed a new method to detect hard exudates with high accuracy relative to the level of injury. In the present method, we first identified candidate exudates lesions using the background ground reduction method. Following the next steps, in the final step of the algorithm, we removed the false exudates lesion results using the decorrelation stretch based method. We tested our algorithm in the publicly available DirectDB database, which contains the basic truth of all images. Compared to current art techniques, we have achieved high performance results for hard exudates lesion level detection with a sensitivity of 0.87, a F7 score of 0.78 and a positive rating of 0.76 (PPV). Ravishankar et.al. [15] proposed a new method to locate the optic disc, where they first identified the major blood vessels and used their division to determine the approximate location of the optic disc. Blurred C-Media Clustering tested several classifiers, including SVM, neural networks, PCA, and general Bayesian classification. Refers to the new control to identify the optic disc, where the major blood vessels are located and the approximate position of the optic disc using their division. It is further localized using color features. We show that many features such as blood vessels, exudates, micro aneurysms and bleeding can be accurately identified with various mutations that are appropriately applied GG Gardener et al. [16] used a back propagation neural network. Exudates area, vascular area, hemorrhage, edema and microanurism area were selected for identification. This was done by analyzing images of one hundred and forty-seven patients with DR and thirty normal retinal images with exudates, retinal images with bleeding

or microaneurysm, retinal images with no blood vessels, and retinal images containing blood vessels. The resulting specificity and sensitivity values are 88.4 and 83.5, respectively. Alireza et al. [17] proposed a partition based on the color representation of the Loves color space and its integration with the best partition using Fuzzy C-Medium (FCM) clustering. They used retina color information for our goals and showed progress through gray scale based technologies. FCM clustering gave an accuracy of 85.6%, a sensitivity value of 97.2 and a specificity of 85.4. A. Mukherjee et al. [18] proposed a supervised learning method to divide a given set of images into 5 classes. Various image processing methods and filters improve many important features, such as the neural use for classification and the automatic, adaptive and innovative approach to image processing and the retina damage that can be easily detected at an early stage. M.W.Khan et al. [19] proposed a work of using several image processing techniques for DR injury detection. Early diagnosis of DR has been found to reduce the risk of vision loss by up to 50%. The image processing methods discussed in this paper can accurately identify DR. The hybrid method should be used to get the best results considering the accuracy and efficiency of DR identification. The various lesion detection methods used for DR also give appropriate results. Image processing methods are evaluated based on these results. One of the serious issues that the entire globe was concerned about was diabetic retinopathy getting the focus of numerous researchers in an effort to identify the best methods for early diagnosis of this condition, which will ultimately avoid early changes in vision. To make the lives of doctors and patients easier, a great deal of research has been done in this area and is constantly being done. A review of numerous studies on diabetic retinopathy can be found in this section [6]. For an extended period, the predominant method for detecting diabetic retinopathy (DR) entailed a two-step extraction and prediction process. Using methods like Hough transform, Gabor filters, and intensity fluctuations, this method usually extracts visual information from color fundus pictures, focusing on areas like blood vessels, the fovea, and the optic disc. Next, in order to locate and identify anomalies such as hemorrhages and exudates, object identification or registration methods such as support vector machines and k-NN were utilized. These conventional techniques have been superseded, though, by more contemporary deep learning techniques that construct convolutional neural networks (CNNs) using designs like AlexNet and GoogleNet. We can see from competitions like those on Kaggle that these CNN techniques perform better in DR detection tasks.



Fig. 3. Diagram of Normal Retinal Image & Abnormal Retinal Image respectively [7]

Even when they work well, comprehension because CNNs are non-linear and non-convex, their operation is still difficult. There have been attempts to visualize CNNs, such as the use of deconvolutional networks to show hidden unit-activated patterns. These approaches do have certain drawbacks, though, namely the inability to summarize patterns and the tendency to concentrate solely on buried levels. While some studies have tackled both classification and object localization tasks, they are still not able to offer a thorough understanding of CNNs. [8]. Automated techniques for detecting diabetic retinopathy (DR) have been based on the extraction of visual characteristics from color fundus photos, with an emphasis on the regions of the optic disc, fovea, and blood vessels. For feature extraction, methods including the Hough transform, Gabor filters, and intensity variations were frequently used. Afterwards, exudates and hemorrhages were identified using object detection or registration methods such as support vector machines and k-nearest neighbors. But deep learning techniques, such as those that use topologies like AlexNet and GoogLeNet, have eclipsed these strategies. Convolutional neural network (CNN) techniques have proven to be superior to conventional methods in recent studies and competitions, such as Kaggle competitions. Because of their intricate structures and non-linear nature, CNNs are still difficult to understand on the inside, even with their effectiveness. There have been attempts to see CNNs in order to understand how they work. Although deconvolutional networks have been suggested as a way to show patterns that are triggered in hidden units, their ability to summarize patterns across layers is limited. In addition to classification, other research has concentrated on object localization tasks, allowing CNNs to anticipate object positions based on class labels. These techniques, though, are still unable to fully disclose CNN's findings. While there have been attempts in recent times to invert representations in each layer of CNNs, these methods simply show what has been preserved at each layer and do not provide a complete explanation of CNN behavior. The concept of class activation maps, which describe weighted activation maps following global pooling layers, is a noteworthy related development. Time series analysis has been added to this idea. This work employs the methodology from is extended to include regression instead of just classification, focusing on the DR detection issue. This method aids in the comprehension and advancement of DR detection methods by illuminating the regions of significance in raw data [9]. The convolutional neural network plays a significant role in the classification of medical images. Sridhar proposed a Diabetic Retinopathy detection system based on a convolutional neural networks architecture. A CNN-based model identified the features of retina fundus images and classified them as DR or no DR and the severity of it. The model was trained on an image dataset that is publicly available on Kaggle. The model achieved impressive results and increased the accuracy in the detection of DR [10].

III. PROBLEM IDENTIFICATION

System uses background and foreground subtraction for masking the unwanted background. It also uses thresholding for segmentation that segments blood vessels by converting

it into binary image. But if eliminating or masking has been done using binarization or black and white intensities value then sensitive information may also erode or eliminate from image that may degrade the correct recognition rate. Background region of the fundus is the portion of the image where no retinal anatomy or lesions present, it consists of only the retinal layer of the fundus so it is an unwanted portion of the fundus image for screening of the DR. The detection of any anatomy or lesion present on the fundus image becomes simple, if it can detect and subtract the background region from the fundus image. By removal of background information we are left with only the retinal anatomy and lesions on the foreground image of the fundus.

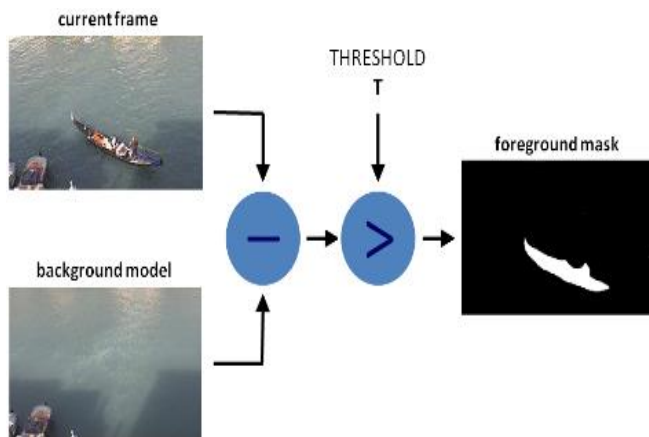


Fig. 4. Background Subtraction[20]

A major task in the field of computer vision and image processing is to detect the foreground and detect changes in image sequences. Background minimization is any technique that allows you to take the front of the image for further processing (image recognition, etc.). Most applications do not require information about the evolution of motion in a video sequence, but only information about changes in the scene, because the areas of interest on an image are objects in front of it (humans, cars, text, etc.). Object localization is required after the image preprocessing phase (which may include post-processing such as image denominating and syntax) that can use this technology. Based on these changes in the foreground, spotting the foreground separates the background from the background. These are techniques that analyze video footage recorded live with a still camera. It works well for object recognition from a general background that does not have complex features. It does not work effectively when it contains useful information in the background, such as blood vessels or nerves that are directly proportional to the accuracy of the system. Diabetic retinopathy requires in-depth monitoring to make a proper diagnosis with prudence and a high level of accuracy in the blood vessels. Diabetic retinopathy is a disease of the retina that affects diabetics and is a leading cause of blindness. It is a disease in which the blood vessels in the retina swell. It can damage the retina of the eye and lead to blindness if the level of diabetes is too high. Diabetic retinopathy affects 80% of people with diabetes for 20 years or more. With proper treatment and eye monitoring, at least 90% of new cases can be reduced. The more diabetic a

person is, the more likely they are to develop diabetic retinopathy. It is a leading cause of blindness in people between the ages of 20 and 64 years. The most effective treatment for the prevention of these eye diseases is early detection by regularly testing the fundus to identify the early symptoms of diabetic retinopathy. The digital fundus camera in ophthalmology gives us digitized data, which can be used to automatically diagnose the disease. Diabetic retinopathy is an eye disease that causes partial or complete loss of vision. Examining these images automatically will help doctors to more accurately diagnose the patient's condition. It emphasizes the determination of retina images using appropriate image processing and data mining techniques.

IV. PROPOSED WORK & IMPLEMENTATION

Proposed work is able to detect Diabetic Retinopathy with less processing time using Sobel edge detection and color scaling technique. Color scaling is a new approach for classifying impairments in an image and changes get more highlighted. Sobel edge detection is gradient edge detection technique that works with horizontally and vertically. Sobel extracts the edges separately from horizontal traversing and vertical traversing then combined both the extractions. It targets sensitive edges and color mapping shows the impairments more precisely. There are various edge detection techniques but sobel is highly sensitive and modern in use as compare to the canny, prewitt and roberts. It works with the kernel for both horizontal and vertical approach. Sobel has various kernels as per the directional ratio and whichever be required can be applied accordingly. The framework for early diagnosis of diabetic retinopathy (DR) by deep learning is illustrated in Figure 5, emphasizing the use of the DenseNet 121 architecture. The efficacy of this design in feature extraction from medical images is what led to its selection, especially in situations where blindness can be prevented through early identification.

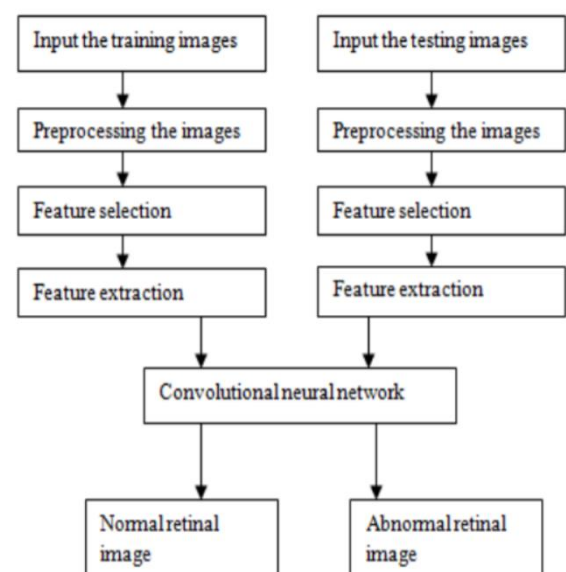


Fig. 5. Block diagram of Workflow[6]

A. Preprocessing

First, an image is taken as input; usually, this is a color fundus photo that shows the retina. A variety of preprocessing methods, such as noise reduction or contrast enhancement, are used to improve significant aspects of the image. The image may be resized and cropped to standardize the input size for efficiency and model compatibility. To guarantee the quality of the dataset, data cleaning procedures are carried out, such as the removal of any black or distorted pictures that could be detrimental to training. In order to rectify imbalances in the dataset, methods such as image rotation and mirroring are utilized to enhance the dataset, guaranteeing a more resilient training procedure. The previously processed photos are changed into numpy arrays, a popular data type that may be used as an input for deep learning models. After processing, the photos are prepared for use in the model's training or testing stages.

B. CNN Model

After preprocessing, a Convolutional Neural Network (CNN) model must be trained. The DenseNet 121 architecture was selected because it has a track record of success in feature extraction from fundus photos and other medical pictures. CNN falls into the category of deep learning, where it mimics how brain neurons actually capture and identify objects. The convolution layer, pooling layer, and fully linked layer are the three layers that make up a CNN. We are employing CNN's Smaller vggnet architecture, which excels at picture categorization and recognition. Using a 3x3 convolution window and max pooling, the vgg network creates a fully connected layer before a softmax classifier [6].

C. Convolutional Layer

Gradient descent is the basis for the bias and weights of the image recognition classifier that is constructed by the convolution layer. This means that there should be less mistake in the activation map that the layer creates and that it should be able to categorize the image correctly [11].

D. Pooling Layer

The pooling layer decreases the output's spatial volume, and we employ Max pooling, which replaces the entire pool with the highest number found in a 3x3 pool created from the picture matrix (the first layer's output). Consequently, we decrease the spatial volume in this manner. We maintain the pool size at 3 by 3 for the first two passes then progressively reduce it to 2 by 2 for the third pass [6].

E. Medical Report

After training, the CNN model can provide medical reports using the input images. The model processes and generates a report when a fresh, unseen image is supplied as a test input. A diagnosis of the degree and existence of diabetic retinopathy in the input image is usually included in this report, which offers medical professionals important diagnostic data. This framework allows for the early diagnosis of diabetic retinopathy, permitting timely intervention to avert vision loss and blindness. It does this by utilizing deep learning techniques and the DenseNet 121 architecture in those who are impacted [11].

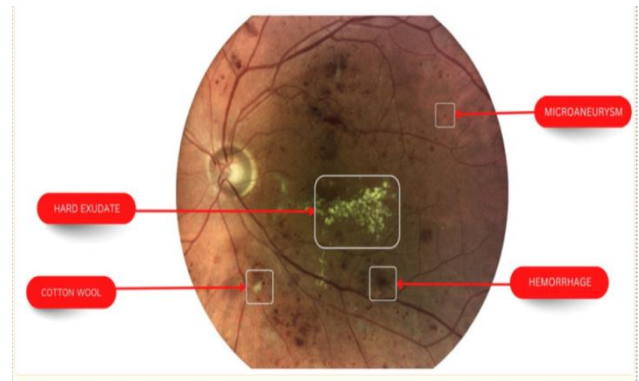


Fig. 6. Diabetic Retinopathy [11]

For pre-processing the data, Image Magick and OpenCV were used. During training, an Intel Core i3 processor with 8GB of RAM was used to support the NVIDIA GeForce GTX 780 GPU with 3GB of RAM. GPU interfacing was made possible using Theano. The Python modules Lasagne and Nolearn were used for the convolutional neural network's design and training.

V. RESULT OUTCOMES

The system has been tested with 100 OCT scanned fundus images of eyes of different patients that belong to infected traits or may not. System recorded 39 as true positive it means that there are 39 images contains diabetic retinopathy and system detected it positively and 43 as true negative that means there is an image contains diabetic retinopathy but system was not able to detect it. There are 2 tests are false negative where diabetic retinopathy has not been there and system didn't detect it as diabetic retinopathy and 3 as false positive where system detected a normal image as diabetic retinopathy which is an error rate of false detection that possess the system for degrading accuracy to 94.25%.

Table No. I Result Analysis

Terms	Outcomes
True Positive	39
True Negative	43
False Positive	3
False Negative	2
Total Testing Class	100

Table No. II Result Comparison

	Kranthi Kumar et al. [14]	Proposed
Modality	OCT	OCT
Method	Background and Foreground Subtraction	DNN
Total Fundus Images	89	89
Result (Accuracy)	87.00 %	94.25%

VI. CONCLUSION & FUTURE SCOPE

These DR detection devices are essential for improving the accuracy of illness diagnosis. Cost-effective automated devices for detecting diabetic retinopathy shorten the time it takes for anomalies to be detected, which aids ophthalmologists in identifying retinal problems. Treatment can be given in a timely manner to prevent problems down the road [3]. The kind of lesions that develop on the retina determines which DR stage a patient is in. This study analyzed the most recent deep learning-based automated methods for the identification and categorization of diabetic retinopathy. We've discussed the common fundus DR datasets that are accessible to the public and provided a quick overview of deep learning methodologies. Because of its effectiveness, the majority of researchers have employed CNN for both DR image identification and classification. Additionally covered in this review were practical methods for detecting and categorizing DR using DL. In this work, we conducted a thorough analysis of different approaches for automatically identifying diabetic retinopathy and tried to develop our own deep learning strategy for the early detection of retinopathy utilizing a DenseNet169. Some picture attributes may be lost due to the multitude of photos taken in varying situations and the extensive preprocessing and augmentation required; therefore, methods that not only retain all the minute but also crucial features should be employed. Additionally, each patient should receive numerous photos, since this would boost the likelihood of accurately classifying the photographs because more information can be acquired than with just two images per individual. The potential the ability to adjust hyper-parameters is continuously increasing as new neural networks are created using more effective pooling techniques. These techniques may be taken into account for upcoming research to determine whether there are any ways to improve performance in this field. Time can effectively complete pre-processing. A better outcome may also be obtained by employing various networks to train the model ensemble. Early identification and precise detection of DR are essential to keep diabetic patients from going blind.

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