Grading and Classification of digital fundus images for Automatic Diabetic retinopathy detection : A Review

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Abstract

One of the main causes of blindness and visual impairment in diabetes patients in developed countries isDiabetic Retinopathy (DR), a prominent chronic disease. According to studies, early detection and treatment can help prevent 90% of instances. Physicians employ retinal imaging to test eyes for lesions associated with this condition. The quantity of photos that must be manually evaluated is getting costly due to the rise of diabetic patients. Additionally, it takes a while to train new employees in this form of image-based diagnosis because it necessitates gaining experience through regular practise. In order to identify non-proliferative diabetic retinopathy, numerous **methods** for spotting micro aneurysms, haemorrhages, and exudates are addressed in this paper. Techniques for detecting blood vessels are also covered for proliferative diabetic retinopathy diagnosis. The report also elaborates on a discussion of the experiments metrics that the scientists used to find diabetic retinopathy. The technical experts and researchers who wish to make use of the current research in this field will benefit from this work.

Keywords: Diabetic Retinopathy, Image Segmentation, Deep Learning, Non Deep Learning, Exudates, Blood Vessels, Digital Fundus Images

1. Introduction

A lot of people have diabetes all around the world. It is the most typical cause of blindness in those under the age of 50. Up to 80% of patients have been affected by this systemic illness for longer than 10 years. Numerous researches agreed that an early diagnosis could prevent the condition in 90% of diabetes people. Diabetes increases the likelihood of developing Diabetic Retinopathy (DR) [1]. Micro blood vessels, which are vulnerable to uncontrolled blood sugar levels, are used to provide blood to all layers of the retina. Circulation arteries begin to collapse as a result of insufficient oxygen delivery to cells when excessive concentrations of glucose or fructose accumulate in the blood. A severe eye damage results from any blockage in these veins. Due to the slowed metabolic rate, DR-interning vasculature have structural abnormalities [2]. DR can be detected early by microaneurysms. Blood vessel size changes as a result of this condition (swelling). Microaneurysms (MAs), exudates (EXs), and haemorrhages (HMs), as well as aberrant blood vessel development, are signs of DR.

Proliferative and non-proliferative DR (PDR and NPDR, respectively) are the two standard stages of DR [3]. When blood vessels in the retina are injured and begin to leak fluid onto

it, NPDR occurs. Retina becomes moist and puffy as a result. At this stage, retinopathy can manifest in a variety of ways, including HMs, MAs, EXs, and Inter RetinalMicro-vascular Anomalies (IRMA). PDR develops when aberrant new blood vessels grow throughout the retina. This complicated form of DR has the potential to compromise eyesight [4]. Since DR is a degenerative condition, early discovery is essential for saving a patient's eyesight and calls for routine screening. The workload on ophthalmologists can be reduced along with the risk of total blindness as a result of DR with the aid of an automated screening method. A Computer-AidedDiagnostic (CAD) system is created for DR screening in order to distinguish between a retina with potential DR and a normal retina [5-7].

2. Progressive stages of Diabetic Retinopathy:

Mild non-proliferative retinopathy: Microaneurysms, or microscopic balloon-like swellings in the tiny blood vessels of the retina, are seen in this early stage of the illness. The fluid from these microaneurysms could seep into the retina. Moderate non-proliferative retinopathy: As the condition worsens, the retina's blood vessels may expand and change their shape. Additionally, they can stop being able to carry blood. Both disorders alter the retina in distinctive ways and may be a factor in DiabeticMacular oEdema (DME) [8-10]. Severe non-proliferative retinopathy: The blood supply to parts of the retina is cut off by the blockage of numerous more blood vessels.Growth factors are secreted by these regions, which instructs the retina to develop new blood vessels. Diabetes with ProliferativeRetinopathy (PDR): At this stage, the retina secretes growth factors that cause the development of new blood vessels, which spread over the retina's inner surface and into the vitreous gel, the fluid that fills the eye.

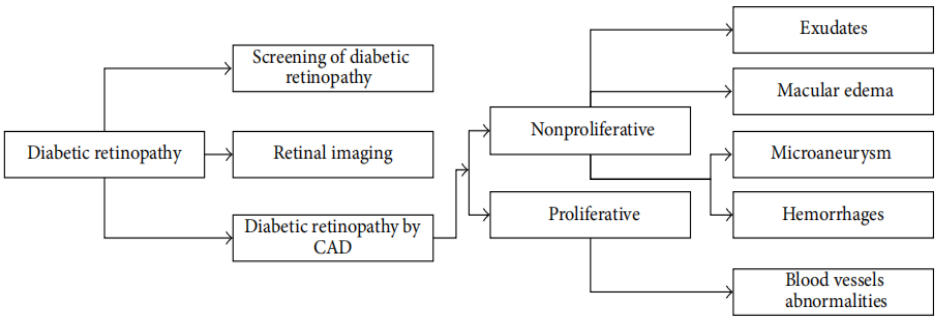

Figure 1: Diabetic Retinopathy progressStages

Due to their fragility, the new blood vessels are more prone to bleeding and rupturing. Retinal detachment, or the ripping away of the retina from underlying tissue, is brought on by accompanying scar tissue contracting, which is similar to wallpaper peeling away from a wall. Permanent vision loss may result from retinal [11-12].

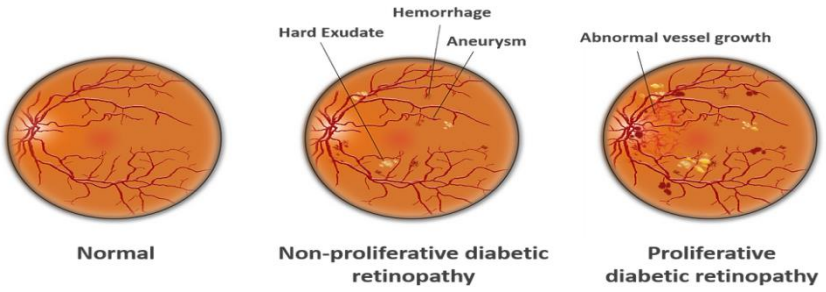

Figure 2: Diabetic Retinopathy- Normal, non-proliferative and proliferative

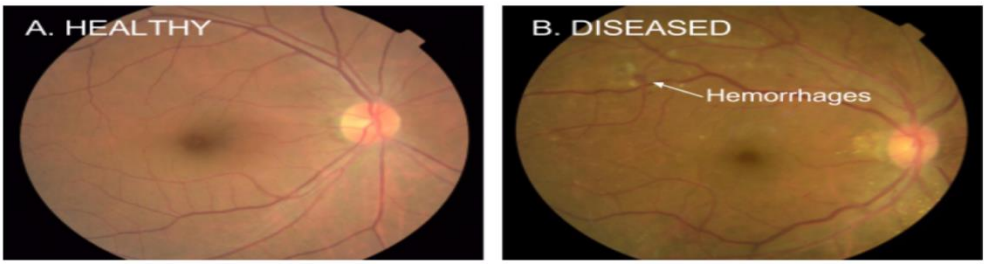

Figure 3.Retinal fundus images in diabetic retinopathy. (A)The retina in the image on the left is healthy, (B) the retina in the image on the right has referable diabetic retinopathy as a result of numerous haemorrhages (red spots) present.

Technical experts and researchers who need to exploit the continuing research in this field will find this work valuable.

3. Classification of Diabetic Retinopathy detection Algorithms:

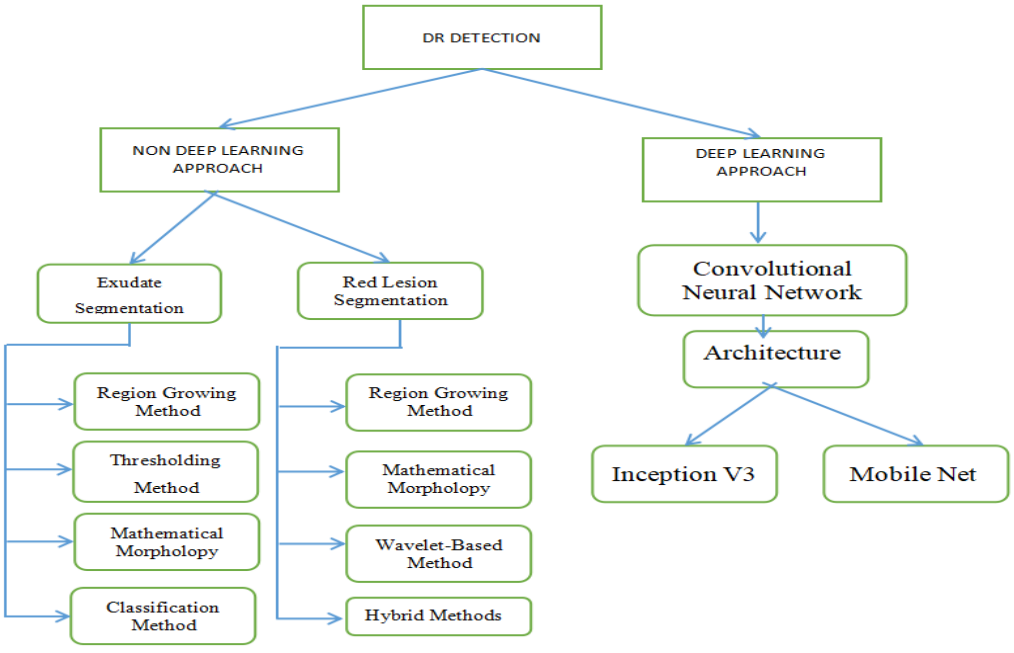

Figure 4: Types of Diabetic Retinopathy detection algorithms

Methodology

Non Deep-Learning Methods:

The majority of non-deep learning strategies include numerous phases. In order to reduce image fluctuation, preprocessing techniques like contrast enhancement are typically performed first. This is done by normalising the raw retinal image. After that, unnecessary anatomical parts like the arteries and optic discs are cut off. For further classification, only the pathological characteristics of DR that remain are preserved.

Two categories of non-deep learning techniques from 2015 or before are exudate (EX) segmentation and red lesion (RL) segmentation [18-21].

Exudate Segmentation: EXs are intraretinal deposits of lipoprotein broughtby vascular leakage. They show up as yellowish lesions with distinct margins on retinal imaging. Patients vary in their shape, size, brightness, and position. Macular edoema (ME), which is the primary cause of vision loss in DR patients, is indicated when clusters of EXs are found in the macular region. To determine DR grading, various scholars proposed the use of a coordinate system based on the location of the fovea.

For the detection of EXs, various strategies have been proposed. Four groups can be made out of them:

- Region Growing Method
- Thresholding Method
- Mathematical Morpholopy Methods
- Classification Method

Red Lesion Segmentation**:** The walls of the retinal capillary vessels have tiny saccular bulges called MAs. MAs appear as circular red dots with a diameter ranging from 10 to 100 m in colour fundus imaging. MAs are hard to tell apart from dot-HEMs, which are slightly larger. The number of MAs and the severity of the DR are directly correlated. MAs are typically the first retinal lesions to manifest in DR. For MAs segmentation by colour picture analysis, several methods have been put forth. Four categories can also be used to group RL detection techniques:

- Region Growing Methods
- Mathematical Morphology Methods
- Wavelet-Based Method
- Hybrid Methods

Deep Learning Methods: By calculating explicit criteria that specialists have specified, algorithms can be created to detect particular lesions or forecast the occurrence of any degree of diabetic retinopathy. By extracting the most predictive features from the images themselves using a large data collection of labelled samples, deep learning is a machine learning technique that reduces the need for such engineering. This method employs the back-propagation optimization algorithm to show how a machine should adjust its internal settings to most accurately forecast the desired output of an image. The publications that use deep learning techniques to build models are listed in the section below.

Convolutional Neural Network

A subset of deep, feed-forward artificial neural networks is the Convolutional Neural Network (CNN). CNNs use a form of multilayer perceptrons called backpropagation, which is intended to require as little preprocessing as possible.

Comparatively speaking to other image classification algorithms, CNNs employ a minimal amount of pre-processing. This implies that the filters, which were manually designed for traditional techniques, are learned by the network. This feature design's independence from prior knowledge and human effort is a significant benefit.

Architectures: Researchers have put forth a variety of neural network topologies over time, each with a different level of complexity and approach. Our dataset of retinal pictures is trained using two alternative architectures, Google's Inception V3 [22] model and MobileNet [23] model. The notion that we must choose between a 3x3 and a 5x5 convolution at each layer of the model serves as the motivation. While bigger convolutions recover highly abstracted characteristics, smaller convolutions recover local features.

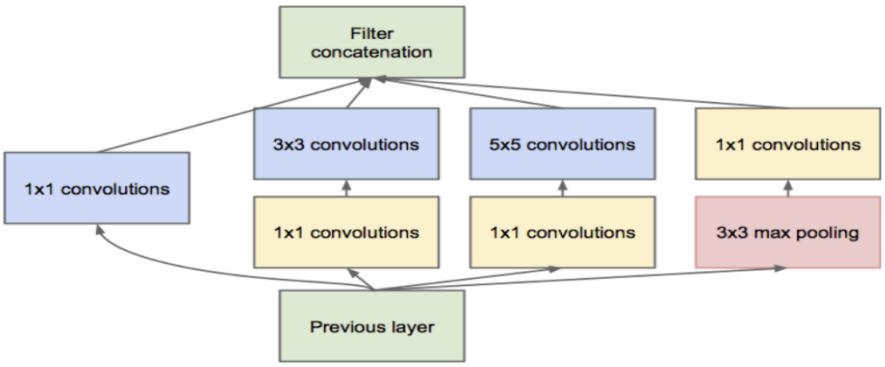

Figure 5: Inception module with dimension reduction.

Therefore, instead of deciding what we want for ourselves, we let the model decide by locating all the convolutions at each layer and selecting the convolution that is best for that layer. Before proceeding, this operation is carried out at each layer. Figure 5 basic inception module provides a quick overview of the actions carried out at each stratum. It is obvious that each layer is doing a wide range of convolutions, as we discussed earlier. The concept is that we don't need to know in advance if it would be better to perform, for instance, a 33 or a 55.

Rather, To delegate all convolutions to the model, which will then select the optimum solution. But in addition to the convolutions, there is also a max pooling layer. Simply because good networks historically included pooling, this was used. This operation was therefore included in order to obtain improved accuracy. However, this architecture also has a significant computational cost issue with larger convolutions that take a long time to compute. As a result, the paper advises using an 11 convolution to reduce the dimensionality of its feature map, then running the resulting feature map through a relu before performing the bigger convolution to remedy the issue. The 11 convolution is important since it makes the feature map's dimensionality less.

MobileNet: An architecture called MobileNet is better suited for vision applications based on mobile and embedded platforms when there is a lack of computing

capacity. [24] Google suggested using this architecture. When compared to a network with regular convolutions of the same depth, this architecture uses depthwise separable convolutions, which dramatically reduces the number of parameters. Deep neural networks that are lightweight are the result. The depthwise separable convolution, also known as depthwise convolution, is used to replace the standard convolution.

Performance Measurement

Toimplement a set of metrics, which are stated below, to monitor how well our suggested method performed in comparison to other ways.At most can use Tensor Board, a performance tracking tool provided by Tensor Flow, for a graphical representation.

The metrics are:

• Training Accuracy: The training accuracy tells us how many of the training photos the model could correctly classify. This is determined by the proportion of training photos that are both true positive and true negative images.

• Validation accuracy: Similar to training accuracy, we calculate the percentage of test images that the model correctly identified as true positive and true negative images. But this time, a separate collection of photos that were not previously used in the training phase were determined to be accurate. This enables us to determine whether our model is over fitted and how well it works for unidentified photos.

• Cross-entropy: This measure of the variance between two probability distributions is frequently utilised. The two probability are more closely related the lower the cross entropy value. According to the equation:

$$H(p,q) = -\sum_{x} p(x) \log q(x)$$

----------(1)

• Runtime: Itneed to keep track of how long it takes the python scripts to execute completely because our suggested solution aims to shorten the training process' runtime without considerably sacrificing accuracy. The runtime comprises the time required to build the unidentified bottlenecks as well as the time required to complete all of the training process' epochs.

Evaluation Index: Sensitivity, specificity, and precision—three indicators—were utilised to assess the experimental findings for situations involving multiple classifications. The chance of being correctly predicted in actual positive samples is known as the True Positive Rate (TPR), while the probability of being correctly predicted in actual negative samples is known as the True Negative Rate (TNR), sometimes known as the recall rate. Precision is the likelihood that positive samples of projected results will turn out as predicted. The area under the curve, or AUC, is a performance indicator used to gauge the accuracy of the classification process.

$$\text{Accuracy(ACC)} : \text{ACC} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{FP} + \text{TN} + \text{FN})}$$

----------(2)

$$\text{True positive rate(TPR)} : \text{TPR} = \frac{\text{TP}}{(\text{TP} + \text{FN})}$$

----------(3)

the proportion of all positive samples that are accurately categorised as positive.

$$\text{True negative rate(TNR)} : \text{TNR} = \frac{\text{TN}}{(\text{FP} + \text{TN})}$$

----------(4)

the proportion of negative class samples among all negative class samples that are correctly classified.

$$\text{Precision(precision)} : P = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

----------(5)

the classifier's determination of the percentage of positive samples in positive examples.

$$F1 \text{ score} : F1 = \frac{(2 \times P \times \text{TNR})}{P + \text{TNR}}$$

----------(6)

Area Under the Curve (AUC)

$$\text{AUC} = \frac{1}{2} \sum_{i=1}^{m-1} (x_{i+1} - x_i)(y_i + y_{i+1})$$

----------(7)

The True PositiveRate (TPR), FalsePositiveRate (FPR), and AreaUnder the Curve (AUC) make up the vertical, horizontal, and AUC axes of the receiver operating characteristic curve, which is a performance metric used to assess the accuracy of classification.

4.Conclusion

Medical imaging plays a major role in assisting with medical diagnosis. Doctors with specialised training must supply the highly specialised competence needed for the examination of medical images. The development of high performance automatic classifiers across a wide range of applications, including for medical diagnosis, is made easier by the introduction of advanced machine learning techniques like deep learning. This paper seeks to investigate novel automatic diagnostic techniques for grading diabetic retinopathy disease, specifically. DR is one of the primary causes of blindness worldwide, as has been previously noted in this study. Early diagnosis can slow the spread of the illness and, as a result, the likelihood of blindness. Ophthalmologists with specialised training in this field analyse retinal fundus images to diagnose DR most frequently. Automatic diagnosis solutions for DR can significantly lower the expenses involved with diagnostics as well as the likelihood that the general public will become blind.This study aids in the early detection of retinopathy; prompt treatment of this condition will prevent irreversible visual loss.

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