Design and Develop A System for Detecting Diabetic Retinopathy Using CNN Model

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Abstract

Diabetic retinopathy (DR) is one of the most threats to diabetes, causing damage and blindness to the retina. It destroys the retinal tissue blood vessels, resulting in fluid leakage and deformation of vision. DR contains four stages (Mild non-proliferative retinopathy, Moderate Non-Proliferative Retinopathy, Severe non-proliferative retinopathy, and Proliferative Retinopathy). Therefore, appropriate screening and treatment at an early point of DR will profoundly avoid serious vision loss. So, this paper proposes a study on an automated diabetic retinopathy detection system which will estimate in which stage is the diabetic retinopathy from eye retina images for diabetic's patients by using deep learning techniques, where we demonstrate the use of Inception V3 a convolutional neural network (CNN) architecture in training fundus image and detecting the DR class. This system has a significant role in the health care sector where it will help the ophthalmologist working in the hospitals in diagnosis diabetic retinopathy and this system will be considered as a functional, time and cost-effective method for automated screening of diabetic retinopathy (DR). Also, we have reported some literature reviews for different research studies and conducted a comparison between three CNNs models which are VGG16, Inception V3, and ResNet-50.

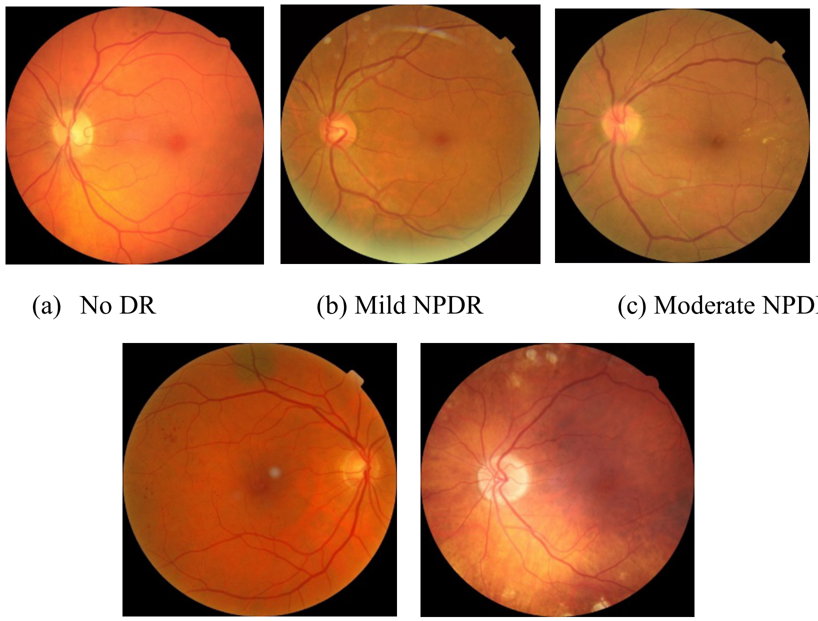
Keywords: Diabetic retinopathy, deep learning, convolutional neural network (CNN), retina image, image preprocessing, Inception V3, VGG16, ResNet-50.

Introduction:

Diabetic retinopathy is one of the most threatening diabetic conditions resulting in permanent blindness in case of delays in treatment. It blocks the blood vessels of the retinal tissue and causes fluid leaking and visual distortion. Around 600 million people are estimated to have diabetes by 2040 and one-third are predicted to have diabetes retinopathy (DR). Early diagnosis of DR is important by regular clinical assessments and early care to prevent vision disability and to improve quality of life (Pao et al 2020). DR has four phases:

- Mild retinopathy: early stages, where microaneurysms can only be found.
- Moderate non-proliferative retinopathy: by that stage, a few of the retina blood vessels are blocked.
- Severe non-proliferative retinopathy causes blood flux deficiency in the retina, as there are blocked further vessels, and hence the retina is given signals for new blood vessel formation.
- Proliferative retinopathy: advanced retinal impulses are rare and fragile and allow new blood vessels to form. They spread to the surface of the transparent glass gel within the eye. When the new retinal blood vessels form and stretch abnormally, their fragile structures can leak and cause serious blindness or vision loss. (Tymchenko et al, 2020)

Early diagnosis is one of the greatest difficulties in treatment effectiveness. Unfortunately, the stage of diabetic retinopathy is very difficult to diagnose accurately, and expert analyses of fundus photographs are required. So, it is critical that the detection stage is simplified, and it will help millions of people.



(a) No DR (b) Mild NPDR (c) Moderate NPDR

(d) Severe NPDR (e) Proliferative DR

Figure 1: Examples of different stages of DR

Problem statement:

Each stage of diabetic retinopathy has its characteristics such that doctors can not recognize some of them and therefore make an incorrect diagnosis. In cases with the right, effective care, and supervision, at least 56% of new cases of illness will be reduced. However, in the first phase of this disease, there are no warning signals, and identifying it early has become a real challenge. Moreover, the diagnostic image of a fundus patient cannot be inspected manually, and the process can only be determined by qualified clinicians.

The DR severity evaluation often involves specialist expertise, and the results of the examination will vary based on classifications (Abramoff et al., 2016). This points to the importance of creating an automated DR solution. Automated image DR assessment systems can provide a clinically accurate and cost-effective diagnosis of diabetic retinopathy and thereby prevent diabetic blindness. In manual scanning, a huge patient fundus image database is challenging and powerless and needs training diagnostic experts. So, manual procedures can be substituted by automatic DR detection systems as the manual effort required for screening can be reduced significantly. Suitable screening and early therapy of DR deeply prevents severe visual damage where the system helps the ophthalmologists in hospitals to diagnose diabetic retinopathy correctly from eye retinal photographs for diabetic patients in the earlier stages. However, deep learning has played a significant role in informing physicians of complications in early diagnosis, providing even more personalized and effective patient treatment. The CNN (convolutional neural networks) are particularly suitable for image analyses. CNN's are designed to process images to enable networks to run and handle larger images more efficiently. Accordingly, it is possible to identify human diseases accurately from medical photographs (Bresnick, 2012). So, we will develop a system that detects diabetic retinopathy automatically by using the CNN model.

Literature review:

Lam et al. (2018) have identified diabetic retinopathy to be the biggest cause of blindness in adults, and early diagnosis is critical for effective treatment. In this paper, the authors demonstrate how colored fundus is used by convolutional neural networks to categorize diabetic retinopathy (CNN) and find that pre-processing of reduced contrast balance in the adaptive histogram and class-labeling testing ensure that data precision improves the comprehension of subtle properties. The paper also defined the AlexNet and GoogLeNet models implementing phases.

A detailed overview of DR detection is provided by Mateen et al. (2020) with about 150 academic publications with three major parts: retinal data sets, DR detection methods as well as success evaluation metrics. Retinal data are addressed first, followed by several methods of diagnosing retinal defects with retinal neovascularization, bleeding, microaneurysm, and exudates. The paper further addresses the significance of evaluation standards in CAD systems.

Pao et al. (2020) presented that entropy images are calculated by using the green portion of the fundus image. In addition, an enhancement of image through unsharp masking (UM) would be used for preprocessing before the calculation of entropy pictures and the CNN-bichannel incorporation of gray entropy and green preprocessing components for UM will increase the DR precision of detection in deep knowledge. This paper reported that retinal pathology identification or diagnosis in diabetic patients can be improved by a deep learning system.

Patel et al. (2016) address different methods to DR recognition and classification, as well as to technological implementation, image data sets, and research resources. Where the automatic DR sensing systems substitute manual methods, manual labor is greatly decreased during scanning and various retinopathic abnormalities are detected by machine learning and image processing.

Qiao et al. (2020) introduced an approach that analyzes the presence of the microaneurysm in a fundus image using convolutional neural network algorithms, which combine deep learning as the principal element of GPU (Graphics Processing Unit) that recognizes the images and segment them more efficient and less time. The authors have therefore provided a segmentation algorithm, which is used to label the image as normal or infect. This provides an automated mechanism to label fundus photographs as mild NPDR, moderate NPDR, and severe NPDR.

Saeed et al. (2021) developed an interactive computer-aided framework for the automatic DR scanning of fundus images using a two-stage transfer learning process with a pre-trained CNN system. The authors have effectively reinitialized the first layer of a pre-trained CNN model, and have used a fully connected layer to exclude discriminatory attributes from fundus images where this phase enables the model to use fundus images to classify DR. The authors finally introduced a discrete curve-dependent classification layer.

Comparison:

To select a CNN model for my project, I have compared between three architecture which are VGG16, Inception V3 and ResNet-50.

1) VGG16 model:

K. Simonyan and A. Zisserman of the University of Oxford introduced the VGG16 (Visual Geometry Group) as convolutional neural network architecture. The architecture fulfills 92,7% one of the top 5 test accuracies of ImageNet, which represents a data collection of over 14 million images from a thousand groups. With the ReLU tradition of AlexNet, the VGG-16 has 13 convolutional and three fully connected layers. The network stacks several layers on AlexNet and uses narrower filters (2×2 and 3×3). A disadvantage of VGG16 architecture is that it requires approximately 500 MB of storage capacity and is more expensive to assess and has about 138 million parameters. (Simonyan and Zisserman, 2014)

2) Inception V3 model:

Inception V3 is a deep convolutional architecture used extensively for classification tasks. In the GoogleNet model, Szegedy implemented the model principle whereby Inception V3 was suggested by upgrading the inception module. There are several symmetric and asymmetric components in the Inception V3 network where every component has multiple branches, average composition, max pooling, concatenation, dropouts, and a fully connected layer. This network has a total of 42 layers and 29.3 million parameters, so that the computational cost is just approximately 2.5 more than GoogleNet. This model achieves 0.937 accuracies, and it requires about 92 MB of storage space which is less than VGG 16. The integration of the lower parameter counts and added regularization with batch-standard auxiliary classifiers and mark smoothing enables high-quality networks to be trained on comparatively modest-sized. (Szegedy et al., 2016)

3) ResNet-50 model:

The core blocks of ResNet-50 (Residual Networks) have two simple architectural principles; the layers have the same number of filters with the same output map size, and when the map size is halved, the number of filters doubles. The down-sample is defined outcomes by convolutional layers, with a two-step normalization, after each convolution and before stimulation of ReLU. The identity option is used if the input and the output are of the same size. The projected shortcut is used to balance the size by 1×1 convolution as the dimensions rise. Total weighted layers are 50, with about 23 million parameters being trained, and ResNet-50 takes up about 98 MB of storage capacity and achieves 0.921 accuracies. (Leonardo et al. 2018)

After discussing these three architectures, we will be using the Inception V3 model in the implementation of a system that detect the diabetic retinopathy.

Research methodology:

A. Dataset:

The image data used in this research was obtained from the data set of Kaggle and it was provided by EyePACS to help researchers at no expense (EyePACs, 2015). The data set includes 88,696 images of 44,348 objects, one image per eye. The photographs in this data set come from a variety of cameras and models and have highly mixed quality. Diabetic retinopathy was classified by a clinician at a scale of 0 to 4 in each photograph as per the magnitude of the international clinical diabetic retinopathy (ICDR):

0 – No DR

1 – Mild DR

2 – Moderate DR

3 – Severe DR

4 – Proliferative DR

We will be using a subset of the Kaggle data set, the subset will contain about 3000 fundus images for all the diabetic retinopathy stages divided into validation images, training images, and testing images.

B. Pre-processing and data augmentations:

The models will be trained and validated with the initial images preprocessed. Preprocessing included image recruitment and resizing. Due to the way APTOS2019 has been obtained, there are unfounded associations between the phase of the disease and several image meta-functions, such as resolution, form, zoom, or total brightness. We will use many augmentations to ensure that CNN does not overload these features and reduce the connections between image quality and their meta-functions. But to standardize the image state we will follow some preprocessed actions. First, we will re-scale the photographs and removed the local average color to have the same radius. The average local color of the photographs will then be mapped to 50% gray and to remove boundary effects, we will clip images to 90% of the original size.

To boost the network position ability and minimize overfitting, we will augment the number of images in real-time. A random augmentation in the images will be done at each stage, maintaining collinearity and range proportions. Random padding, shift to an RGB value, zooming, rolling, and rotating will be applied and these changes are especially effective in the first stage of the diseases, which is considered as the most complicated stage to classify and the least numerical.

C. *Transfer learning:*

Transfer learning refers to the application of an architecture already trained on other photographs, the convolutional neural networks (CNNs) are particularly suitable for image processing and the Inception V3 model has been adopted for this research based on its deep architecture. It has both width and height enhanced by its size. Inception both addresses the issues of a big model by eliminating fully connected layers and adding small layers even within the convolutions, including overfitting due to a wider variety of parameters and the wide need for computing capital to improve the network size. (Masood, 2017)

In order to minimize network parameters, Convolution factoring substitutes larger convolutions with many smaller convolutions, whereas auxiliary classifiers provide regularization impact to the network. Networks of Inception are notorious for using Inception modules. The Inception modules help to extract characteristics of the same class of images that vary in size. The Inception module definition in DR classification is beneficial since the characteristics of DR normally vary in size. In addition, a Relu-activated layer will be included in the top of pre-trained models accompanied by the SoftMax classifier to distinguish extracted properties. Then, we will load and delete the old final layer of the pretrained model and train a new one for eye photographs. Therefore, 5 main groups referring to no DR, mild NPDR, moderate NPDR, severe NPDR, and PDR have been changed to the last fully connected layer. The data used for training and validation are separate from each other and the data used during training is tested again after the learning process to see how much learning is kept. Moreover, a validation accuracy is the percentage precision of predictor the class of images randomly selected from test data not used in the training process. (Li et al., 2019)

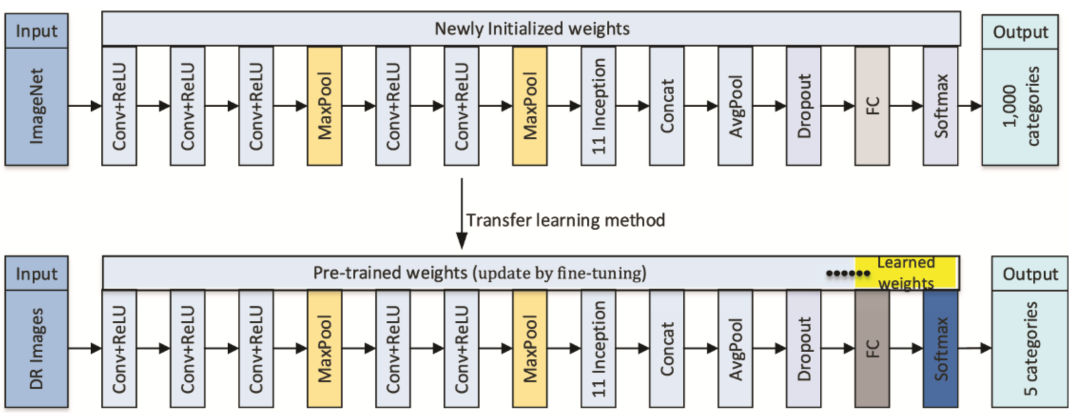


Figure 2: Deep transfer learning schema of network Inception-v3. (Li et al., 2019)

Future work:

The automatically diabetic retinopathy detection system will be implemented and coded using the python programming language. One of our limitations is the number of images in the dataset is not sufficient and this number of datasets has been chosen because more data mean more time for the model to be trained, more storage space, and therefore a high-performance device for implementation, so we are planning to obtain a device with a better property and increase the number of images and therefore the classification accuracy will be increased. The system can also be expanded to an online platform and used to assist patients in regions in which diagnostic testing is hard to carry out and qualified doctors are difficult to locate to evaluate the image and diagnose the disease. So, they can the online system to automatically test the eye retina image to detect the phase of diabetic retinopathy so before the disease degrades, they can start therapy.

Conclusion:

We proposed a study on a system that detects diabetic retinopathy automatically from eye retina images. The proposed system will analyze the presence of a microaneurysm inside the fundus photograph using a convolutional network (CNN) algorithm that uses deep learning to enhance preprocessing and data augmentations, after that use inception v3 model to train the images to detect the DR class and check the validation accuracy. In this framework, the automatic testing of diabetic retinopathy (DR) would be considered as a practical, timely, and cost-effective method to help the ophthalmologists identify fundus images mild NPDR, moderate NPDR, severe NPDR, and Proliferative DR. Also, we have demonstrated the future work that can be applied to improve our system.

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