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Automated Diabetic Retinopathy Detection using Deep Learning

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Abstract. Diabetic retinopathy (DR) is a retinal blood vascular disease caused due to diabetes mellitus. Being the leading cause of blindness, it becomes utmost important to detect DR. There is variety of reports on automatic detection of DR and most of them are dependent on the segmentation and feature extraction algorithms of various clinical signs of DR. The classification results of such methods relay on the performance of segmentation and feature extraction methods. In this paper, we have proposed a deep learning based approach to automatically detect DR. We exploited the architecture of classical Convolutional Neural Network (CNN) to learn the features of DR from the color fundus image. The convolution layers in the CNN learn the normal and abnormal features from the retina image itself. This proposed two-class classification approach using CNN detects the DR and normal images with a high accuracy of 98.7%.

Keywords; retina; diabetes; retinopathy; deep learning; convolution

1. Introduction

Diabetes is a chronic disease, which occurs due to increase blood sugar level in the body. It slowly affects the circulatory system including that of the retina. The high blood sugar damages the blood vessels of retina over the time causing the Diabetic Retinopathy (DR). According to the World Health Organization, 135 million people are affected by diabetes mellitus worldwide and by the year 2025, this number will increase to 300 million [1]. Early detection of DR can enable timely treatment and stop complete vision loss [2]. Fig.1 shows the DR image with its typical clinical features like microaneurysms, hemorrhages, exudates and cotton wool spots.

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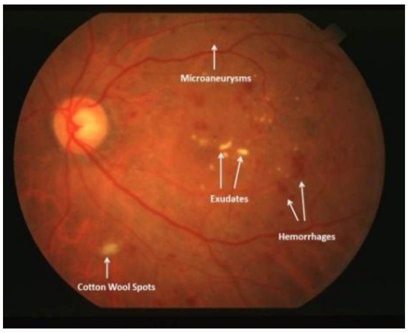


Fig 1. DR affected retina with visible clinical signs

Diabetic retinopathy can be non-proliferative DR (NPDR) or proliferative DR (PDR). The ophthalmologists usually recognize diabetic retinopathy based on features, such as blood vessel areas, exudates, hemorrhages, microaneurysms, and texture. The incidence of microaneurysms in the eye is one of the early signs of diabetic retinopathy. There are a number of reports on automatic detection systems for DR that are based on one feature or combination of multiple clinical features [3-4]. In this paper, we propose a deep learning based approach for automatic detection of DR. Here, our main focus is to distinguish DR from normal image. We exploited the advantages of Convolutional Neural Network (CNN), which is vastly used in object and pattern recognition. Use of CNN discard the need of hand designed feature extraction methods. It extracts the features form the raw image pixels and gives classification results based on the learned features. We have used basic Convolutional Neural Network (CNN) for our initial experiments and it can effectively detect the DR affected retina with a high accuracy of 98%.

This paper has been arranged as follows: section II describes state-of-the-art of two class classification of DR, the proposed Convolutional Neural Network based method is explained in section III, the experimental results are explained in the section IV followed by the section V with drawn conclusion.

2. State-of-the-Art

In the past ten years, several research works were conducted in the development of automated DR diagnosis. The aim of the Computer Aided Detection system is to discriminate normal and DR using different clinical features like microaneurysms, hemorrhages, exudates, blood vessels, node points, and textures etc. Most of the existing works are mainly dependent on the segmentation and feature extraction methods for proper classification. Some of the methodologies are reviewed for two class classification (normal and DR) as follows:

Some of the popular DR Screening tools are developed by Usher et al. [5], Sinthanayothin et al. [6], Aptel et al. [7], Reza and Eswaran [8], Gardner et al. [9], Kahai et al. [10], Osareh et al. [11] and Quellec et al. [12] using clinical features namely blood vessels, exudates, Cotton Wool Spots, Microaneurysms, and Hemorrhages.

Jelinek et al. [3] have proposed an automated DR detection based on microaneurysms. Their method is based on the automatic microaneurysms detection system proposed by Spencer [17] and Cree [18]. This combined method attained a sensitivity of 85% and specificity of 90%.

Sinthanayothin et al. [6] used adaptive intensity thresholding and a moat operator to enhance the edges for increasing the contrast of the lesions. They detected blood vessels using the matched filter on the basis of three properties and then detected hemorrhages using tracking method. A recursive region-growing segmentation algorithm is used to segment the red lesions and then a neural network was used to excerpt the retinal blood vessels from Hemorrhages. All the features are finally fed to the NN and detect DR. Their method attained a sensitivity of 80.21% and specificity of 70.66%.

Aptel et al. [7] evaluated the effect of one and three field, mydriatic and nonmydriatic in digital fundus photography for screening of DR. They evaluated the four methods and obtained kappa value of 0.95. Reza and Eswaran [8] used a rule based classifier for detection of bright lesion and reported an accuracy of 97%.

Gardner et al. in [9] proposed an automated DR detection using pixel intensity and a back propagation neural network to detect microaneurysms and hemorrhages. Their method obtained a sensitivity of 88.4% and specificity of 83.5%.

Kahai et al. [10] have used morphological features and Bayesian framework to classify the lesions for automated DR detection and reported a sensitivity of 100% and specificity of 67%. Osareh et al. [11] have classified the two classes using Fuzzy C-Means Clustering with an accuracy of 90.1%.

Quellec et al. [12] have used optimal filters to segment out microaneurysms and used neural network for DR classification with Area Under Curve (AUC) of 0.927.

Usher et al. [13] used neural network to detect the microaneurysms. The dark lesions were extracted using moat operator and the Exudates were extracted using Recursive Region Growing (RRGT) and adaptive intensity thresholding. For this method, the sensitivity of detecting the microaneurysms is 95.1% and specificity is 46.3%.

Neubauer et al. [15] and Suthammanas et al. [14] introduced the automated tele-screening system using Retinal Thickness Analyzer (RTA) and exudates respectively. In [15] the use of RTA achieved a mean sensitivity of 93% for PDR. In [14] exudates were detected with an accuracy of 92.52%.

Larsen et al. [16] have provided an automatic detection method DR and used visibility threshold to extract the red lesions. Their system can classify DR and Normal retina with accuracy 90.1% and 81.3%.

Hansen et al. [19] considered the red lesions as feature and proposed an automated DR screening method. Their method was based on Larsen et al. [16] red lesion detection method and reported a sensitivity of 100%.

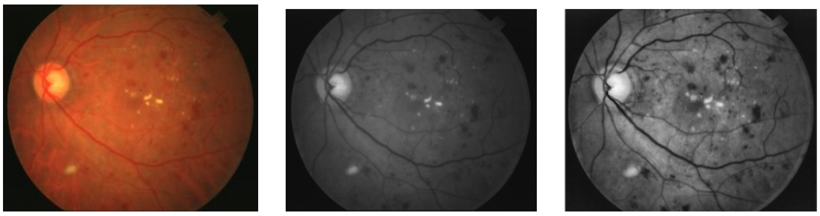
Dupas et al. [20] have developed a Computer Aided Diagnosis (CAD) system for grading DR. The features such as microaneurysms, hemorrhages, exudates were used and coupled with k-NN classifier to detect DR. The obtained sensitivity is 83.9% and specificity is 72.7%.

3. Proposed Deep Learning Method

In this paper, we propose a deep learning based method for DR detection. We have exploited the advantage of Convolutional Neural Network for detecting DR affected retina image. The Convolutional Neural Network is the advanced version of the general Neural Network (NN) used in various areas, including image and pattern recognition, speech recognition, natural language processing, and video analysis [21]. The CNN facilitates the deep learning to extract abstract features from the raw image pixels. CNNs take a biological inspiration from the visual cortex. The visual cortex has lots of small cells that are sensitive to specific regions of the visual field, called the receptive field. This small group of cells functions as local filters over the input space. The CNN architecture consists of four types of layers: convolution layers, pooling/subsampling layers, non-linear layers, and fully connected layers [22]. For image recognition, CNN accepts an image as input. Then, a series of convolution and pooling operators are performed on the input image to extract low to high level features. At the final stage, the outcome of the last convolution layer is connected through the full connection layer. The outcome of the fully connected layer is the CNN output. The number of output nodes is equivalent to the number of image classes [23]. The proposed DR detection method is an image based method and consists of two phases: Image pre-processing and Classification.

A. Image Pre-Processing

Before feeding the retina image to the CNN, we performed pre-processing to enhance the quality of the image. All the retina images are converted into TIF format and resized into a standard image size 60×60. After converting all the images into 60×60 TIF format, we extracted the green channel as it provides the distinct visual features of the retina compared to other two channels. Then, an Average filter of size 5×5 is applied to remove the noise. After that the contrast of that grayscale retina image is enhanced by applying Contrast-limited adaptive histogram equalization (CLAHE). The image pre-processing steps are shown in Fig.2.



(a) (b) (c)

Fig 2. Image Pre-processing Steps: (a) Color fundus image, (b) Green Channel, (c) Enhanced Image

B. CNN Architecture

We have exploited the architecture of the LeNet5, which is the first CNN used for identifying digits. The general structure of LeNet5 is as follows:

Input=>Conv=>Pool=>Conv=>Pool=>FC=>ReLu=>FC=>Output

To work with the retinal images, the parameters and hyper-parameters are adjusted as we want the network to be able to perform DR classification by looking for low level features such as edges and curves, and then building up to more abstract concepts through the series of convolution layers. In the convolution layer of CNN, small filters are convolved on the image. Let's consider $f(x, y)$ is an image and $g(x, y)$ is a filter convolving the image, mathematically it can be expressed as follows:

$$(f * g)(x, y) = \sum_{u=-\infty}^{+\infty} \sum_{v=-\infty}^{+\infty} f(u, v).\, g(x - u, y - v) \quad (1)$$

The kernel/filter slides to every position of the image and computes a new pixel as a weighted sum of the pixels it floats over.

In our application, the input image size is 60×60 and to process the whole input image, the receptive field size in each convolution layer is kept 9×9. In the first convolution layer, the number of filter is kept 60. The first convolution layer extracts features like curves and edges of optic disc and vascular structure. The second convolution layer looks for the higher level features, like shape of the optic disc, structure of blood vessels using more filters. Keeping the filter's size same, the numbers of filters are increased to 490. There is a 3rd convolution layer that acts like a fully connected layer as the in this layer, the filter size is kept same as the input volume outputted from 2nd pooling layer. Here, the numbers of filters are increased to 1024.

After each convolution layer, a pooling layer is added to down sample the features. It makes the features robust against noise and distortion. The intuitive reasoning behind this layer is that once we know that a specific feature is in the original input volume (there will be a high activation value), its exact location is not as important as its relative location to the other features. This layer drastically reduces the spatial dimension of the input volume. The pooling layer basically takes a filter and a stride of the same length. It then applies it to the input volume (output of a convolution layer) and outputs the maximum number in every sub-region that the filter convolves around. Here, the 2 max-pooling layers of size 2×2 use following equation to down-sample the features:

$$x_j^l = f(\beta_j^l \max\left(x_i^{l-1}\right) + b_j^l) \tag{2}$$

where β_j^l is a weight and b_j^l is bias.

A non-linear layer, Rectified Linear Unit (ReLU), is added after last convolution layer to add non-linearity in the data as the real world data are non-linear in nature. A ReLU is an activation function that turns all negative activations into positive and keep the output size same as the input. It also helps to train faster. A ReLU performs a function:

$$R(y) = \max(0, y) \text{ where } y = Wx + b \tag{3}$$

i.e. if $y < 0, R(y) = 0$ and if $y > 0, R(y) = y$. The major benefits of ReLUs are sparsity and a reduced likelihood of vanishing gradient.

The final Fully Connected Layer (FC) is a traditional Multi-Layer Perceptron that uses a Softmax activation function in the output layer. The purpose of the last FC layer is to use high level features represented by the convolution and pooling layers, and compute the correct probabilities for classifying the input image into various classes. Now, we have 2 target classes, viz, DR and Normal retina. So, the last fully connected layer takes the 1024 features from the previous layer and checks the rank of the input test image and classify into one of the 2 classes. The network learns all the features using proper training. The network architecture for DR detection is shown in Fig. 3.

4. Experimental Results and Discussion

In this study, we have collected DR and Normal images from the MESSIDOR [24] and STARE [25] databases. For a balanced training, the CNN is trained with 300 DR-

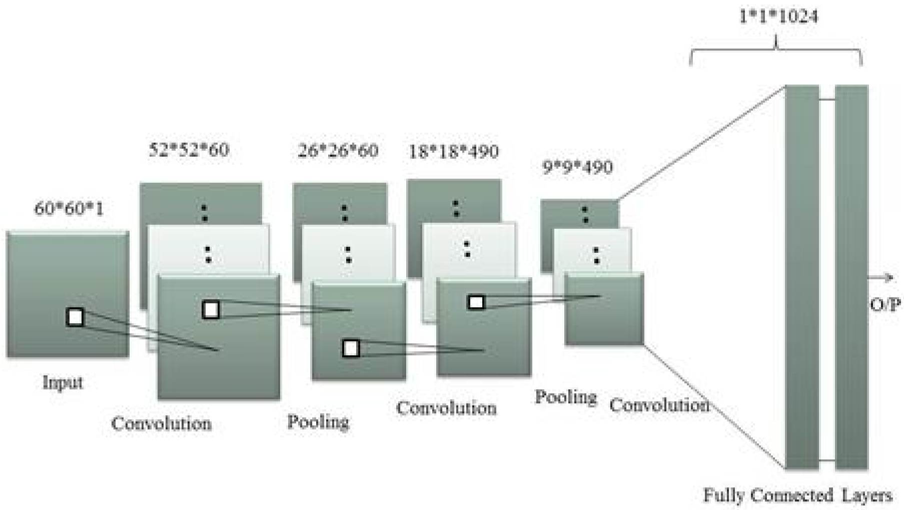


Fig 3. Classical CNN architecture for DR Detection

(NPDR and PDR) and 200 Normal grayscale images of size 60×60. Keeping the convolution filter size 9×9, the numbers of filters are kept 60, 490 and 1024 in the consecutive layers. The training is done with an epoch 50. For each training epoch we provided a batch size of 9 training images and 1 validation image. For 2-classes, we have tested 42 DR images and 33 Normal images. The CNN has achieved a high accuracy of 98.7%. Each test produces a score for each image while comparing to each target class. If the score between test image and one of the target classes is larger than the other class, then that class is recognized in the first rank. Here, out of 75 test images, 74 images are correctly recognized, hence the recognition rate for rank 1 is 98.7%. We further evaluated the performance in terms of sensitivity, specificity, positive predictive value and negative predictive value. The Sensitivity measures the percentage of the people actually having the disease diagnosed correctly. In our experiment we achieved Sensitivity of 100%. That means all the DR images are detected correctly. The Specificity measures the percentage of the people not having disease diagnosed correctly. In our experiment, one normal image is incorrectly detected as DR image; hence, we obtained the specificity of 97%. The positive predictive value is the probability that subjects with a positive screening test truly have the disease. We got a positive predictive value 97.7%. Negative predictive value is the probability that subjects with a negative screening test truly don't have the disease. We obtained negative predictive value 100%. Table I shows the performance evaluation of the proposed CNN method. Table II shows the comparison of the proposed method and existing binary classification method for DR detection. The proposed deep learning method outperforms most of the existing conventional 2-class classification methods.

TABLE I. PERFORMANCE EVALUATION OF THE PROPOSED DEEP LEARNING APPROACH

Accuracy	Sensitivity	Specificity	Error Rate	Positive Predictive Value	Negative Predictive Value
98.7%	100	97%	1.33%	97.7	100%

TABLE II. PERFORMANCE COMPARISON OF EXISTING METHODS AND PROPOSED METHOD

	Features	Methodology	Database	Performance Measure
Suthammanas et al. [14]	Exudates	DR telescreening system	Private Hospital	Accuracy- 92.52%
Dupas et al. [20]	MA, HA, and exudates	k-NN classifier	Messidor	Sensitivity- 83.9% Specificity- 72.7%
Quellec et al. [12]	Optimal filter frame work	k-NN	Hospital database	AUC- 0.927
Reza and Eswaran [8]	Hard exudates , CWS , and large plaque of hard exudates	Rule based classifier	STARE	Accuraccy- 97%
Ashraf et al. [26]	Red lesions	Local Binary Pattern, SVM	DIARETB1	Accuracy- 86.15% Sensitivity- 87.48% Specificity- 85.99%
Sinthanayothin et al [6]	Red lesions	Neural Network	Private Hospital	Sensitivity- 80.21% Specificity-70.66%.
Proposed Method	Image pixels	Convolutional Neural Network	Messidor, STARE	Accuracy- 98.7% Sensitivity- 100% Specificity- 97%

5. Conclusion

In this paper, we have proposed a binary classification of DR using Convolutional Neural Network. The CNN takes grayscale preprocessed images and recognizes the retina image affected by Diabetic Retinopathy and the normal retina image. We have achieved a high accuracy of 98.7%. The proposed method is an image based method which is quite practical to implement. The advantage of this system is that there is no requirement of extra feature extraction step. The convolution layer serves both as feature extractor and the classifier. CNN can also cope with the distortions such as change in shape due to camera lens, different lighting conditions, different poses, presence of partial occlusions, horizontal and vertical shifts, etc. In future, we will work on detecting different stages of DR.

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